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Abstract

Broad-scale political and socio-economic conditions are powerful determinants of land use change. Yet, their relative importance is unclear. The main goal of this thesis was to increase the understanding of such broad-scale drivers of land use change by studying how Eastern Europe's landscapes were affected by the political and socio-economic transition after the fall of the Iron Curtain in 1989. The border triangle of Poland, Slovakia, and Ukraine in the Carpathians was selected as a study area, because cross-border comparisons of land use change allow for decoupling overall trends in the transition period from country specific changes. Moreover, the Carpathians are of exceptional ecological value, but little is known about land use effects on these ecosystems after 1989. Post-socialist land use change was quantified based on Landsat TM/ETM+ images by (1) comparing contemporary (year 2000) landscapes among countries, and (2) using images from 1986 to 2000 to investigate whether differences originated from socialist or post-socialist land use change. Results indicated that forest change, farmland abandonment, and farmland parcelization were widespread in the transition period, likely due to worsening economic conditions, weakened institutions, and societal change. However, land use trends also differed strongly among the three countries due to dissimilar land ownership patterns, land management practices, and land reforms. Poland and Slovakia converged in the transition period in terms of land cover, while Ukraine clearly diverged. This thesis provided compelling evidence of the importance of economic and institutional change for land use change and underpinned the pivotal role of ownership patterns and land management policies. These factors were important to understand land use change in Eastern Europe, and they are likely equally important elsewhere.

Zusammenfassung

Politische und sozioökonomische Rahmenbedingungen haben entscheidenden Einfluss auf Landnutzungswandel; die relative Bedeutung dieser Faktoren untereinander ist jedoch oftmals unklar. Ziel dieser Arbeit ist es, durch die Untersuchung der Auswirkungen der politischen und sozioökonomischen Transformation auf Landnutzungswandel in Osteuropa zu einem besseren Verständnis solcher übergreifenden Einflussfaktoren beizutragen. Am Beispiel des Dreiländerecks Polen-Slowakei-Ukraine in den Karpaten wurden hierzu grenzüberschreitende Landschaftsvergleiche durchgeführt, da solche Vergleiche die Entkopplung der Faktoren allgemeiner Landnutzungstrends von Faktoren länderspezifischer Veränderungen ermöglichen. Darüber hinaus sind die Auswirkungen postsozialistischen Landschaftswandels auf die Karpaten, einem Gebiet mit einzigartigem ökologischen Wert, bisher weitestgehend unerforscht. Mit Hilfe von Landsat TM/ETM+ Satellitendaten aus dem Jahr 2000 wurden rezente Landschaftsunterschiede zwischen Ländern quantifiziert. Auf der Basis von Bildern von 1986-2000 wurde anschliessend überprüft, ob Länderunterschiede auf sozialistischen oder post-sozialistischen Landschaftswandel zurückführbar sind. Die Ergebnisse dieser Analysen zeigten weit verbreiteten Landnutzungswandel nach 1989 als Folge von sich verschlechternden wirtschaftlichen Bedingungen, geschwächten Institutionen und gesellschaftlichem Wandel. Die Länder unterschieden sich jedoch auch deutlich hinsichtlich Forstveränderungen, Brachfallung und Parzellierung von Ackerland. Diese Unterschiede lassen sich durch verschiedene Besitzverhältnisse, Bewirtschaftungsformen und Landreformen erklären. Während sich Polen und die Slowakei landschaftlich seit 1989 annähern, entfernt sich die Ukraine zunehmend. Diese Arbeit unterstreicht die Bedeutung ökonomischer und institutioneller Veränderungen für Landschaftswandel und zeigt, wie unterschiedliche Besitzstrukturen und Landreformen Landschaftswandel beeinflussen.

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Chapter I:
Introduction

1 Changes in the earth system and the role of land use

Profound transformations in the earth system are becoming increasingly apparent from local to global scales (MEA 2005). For example, the composition of the atmosphere is now considerably different from what it was centuries ago. The build-up of CO_2 and methane leads to climate warming, changes the Earth's air and water cycles, and ultimately threatens the basic functioning of the earth system (Steffen et al. 2004). There is now compelling evidence that global environmental change is largely due to the activities of people. Humans have altered most terrestrial ecosystems (Vitousek et al. 1997) and no place on the planet remains unaffected by human influence (Sanderson et al. 2002). More than 50% of natural ecosystems have been domesticated for direct human use (Kareiva et al. 2007), the majority of the world's fisheries are overexploited and close to collapse (Worm et al. 2006), human activities cause global biodiversity decline at unprecedented rates (Pimm and Raven 2000; Gaston 2005), and today's greenhouse gas levels are largely connected to population growth and increased economic activities during the last 150 years (Steffen et al. 2004).

At the same time, the consequences of these changes for ecosystems and people's livelihoods are of growing concern (Steffen et al. 2004). There is increasing awareness about the complete dependence of humanity on the Earth's ecosystems and the services they provide (e.g., food, water, disease management, climate regulation, or recreation potential), that many of these ecosystem services are highly vulnerable to changes in the earth system, and that a number of services are currently being used at unsustainable rates (MEA 2005). Analyzing the human ecological footprint, the area of land needed to provide resource consumption in a sustainable way, revealed that current use of ecosystem services exceeds the Earth's capacities by about 30% (Wackernagel et al. 2002). This is largely due to overexploitation and because ecosystems have been domesticated to maximize the provision of some services (e.g., food production) while others have been neglected (e.g., natural hazard mitigation) (Foley et al. 2005; Kareiva et al. 2007). Both, the alarming impact of human activities on the earth system and the enormous feedbacks of these changes for human well-being, underpin the need for a greatly improved understanding of the coupled human-environment system, and for including the human dimension as a basic element of the earth system (Turner II et al. 2003; Moran and Ostrom 2005; Haberl et al. 2006).

People dwell on land and the vast majority of human activities focus on terrestrial ecosystems. The land sub-system is therefore central for studying how people interact with their environment, for understanding how these interactions relate to global environmental change, and for assessing the consequences of these interactions for ecosystem services and livelihoods (GLP 2005; Lambin and Geist 2006). Land use is defined as the purpose for which humans exploit the Earth's surface (Turner II et al. 1995; Lambin et al. 2006). Land use change has become the primary driver of change in the earth system, either by converting natural landscapes for human purposes or by changing management practices in human-dominated landscapes (Foley et al. 2005; GLP 2005). These changes have enabled the highly efficient provision of particular ecosystem services that are essential for humanity (e.g., food, fiber, shelter, freshwater, MEA 2005). For instance, agricultural intensification and cropland expansion led to a huge increase of the world's food production in the second half of the 20th century (Matson et al. 1997). Overall, humans have therefore benefited greatly from land use change. However, some land use changes also degrade the global environment, lead to the loss of other important ecosystem services, and potentially undermine the long-term capacity of ecosystems to provide services (Foley et al. 2005; Bennett and Balvanera 2007). For example, land use played a major role in changing the global carbon cycle and has contributed to climate change (Houghton 1999; Houghton and Goodale 2004). Anthropogenic nutrient inputs from fertilizers and atmospheric pollutants have widespread effects on water quality in coastal and freshwater ecosystems (Matson et al. 1997; Bennett et al. 2001). Land use is also an important agent of land degradation and desertification (Reynolds and Stafford-Smith 2002) and the destruction, modification, and fragmentation of habitat is the main cause for extinctions (Sala et al. 2000; Loreau et al. 2001). Moreover, changes in land use promote the spread of pests and diseases (Patz and Norris 2004), and determine the resilience and vulnerability of places and people (Turner II et al. 2003; Kareiva et al. 2007).

Local land use decisions have therefore an increasing impact at the global level (Foley et al. 2005). *However, the understanding of what drives these decisions is far from complete* (GLP 2005; Lambin and Geist 2006). Saying this does not deny that there have been major advancements in unraveling the coupled human-environment system on the land (Gutman et al. 2004; Rindfuss et al. 2004). Two decades of land use change science have deepened the understanding of how land use decisions are made considerably, particularly by synthesizing from a large number of case studies (Geist and Lambin 2002, 2004; McConnell and Keys 2005). Yet, these meta-analyses have also shown the complexity of land use decisions and led to the de-mystification of several over-simplistic paradigms. For instance, poverty and population growth were long thought to be the primary drivers of tropical deforestation, but macro-economic conditions, in-migration, or infrastructure development often outrank these factors, and drivers of tropical deforestation differ considerably among different regions in the world (Angelsen and Kaimowitz 1999; Lambin et al. 2001). The richness of explanations of land use change has increased noticeably, mainly at the expense of the generality of these explanations (Lambin et al. 2006). Overall however, the understanding of the drivers of land use decisions still remains weak.

The problem is that local land use decisions are determined by a multitude of factors that themselves operate at a variety of often nested scales (Geoghegan et al. 2001; Lambin and Geist 2006). These scales range from the level of local characteristics (e.g., soil fertility) and actors (e.g., individuals, households) to the level of global conditions (e.g., macro-economy, trade agreements) and decision makers (e.g., governments). Separating *proximate causes* of land use change from their *underlying driving forces* is a useful concept for understanding how these scales interact (Turner II et al. 1995; Geist et al. 2006). Proximate (or direct) causes generally operate at the local scale and include land use activities at a particular location (e.g., agricultural expansion, logging, or urbanization).

These activities themselves are constrained by underlying (or root) driving forces that determine the demand for specific land use activities. Some of these driving forces originate from the local level, for example fine-scale biophysical variability, household numbers, or local land use history (Pfaff 1999; Geoghegan et al. 2001; Fox et al. 2002; Liu et al. 2003; Entwisle and Stern 2006). However, the vast majority of underlying driving forces of land use decisions originate from the regional or global level, and include for example, demographic, socio-economic, political, institutional, technological, cultural, and broad-scale biophysical factors (Brookfield 1999; Geist et al. 2006). These broad-scale conditions constitute the framework for local land use decisions. Moreover, changes in broad-scale boundary conditions frequently result in changing demand for land use activities, thus influencing proximate causes at the local scale, which in turn triggers land use change and ecosystem dynamics (Geist et al. 2006, Figure I-1).

This relationship is relatively well-studied at a general level and a number of studies have demonstrated the paramount importance of broad-scale boundary conditions for local land use decisions (Dietz et al. 2003; Tucker and Ostrom 2005; Geist et al. 2006). For example, institutions and policies exert a huge influence on people's land use decisions through subsidies, land management policies, or property rights, to name only a few (Kaimowitz et al. 1999; Mertens et al. 2000; Sunderlin et al. 2001). However, separating out the effects of specific underlying drivers or assessing the importance of different broad-scale driving forces relative to each other is challenging, and the understanding of how changes in broad-scale conditions affect rates and spatial patterns of land use change is weak (GLP 2005). This lack of understanding is mainly because broad-scale factors are often constant or change only gradually at the time scales commonly studied (i.e., a couple of years or decades), and altering the framework of broad-scale factors experimentally is not feasible.

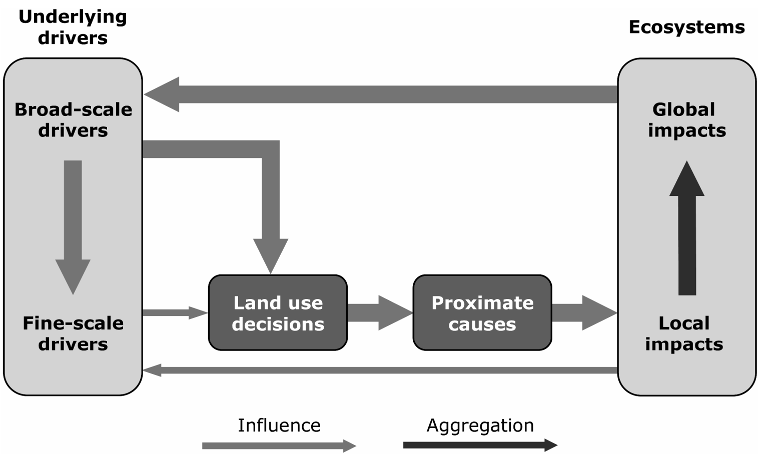

Figure I-1: Simplified scheme of scale-dependency in land use decision making and the impacts of land use change on ecosystems. Underlying drivers of land use change operate at different scales and influence land use decision at the local level. This controls proximate causes which in turn affect ecosystems. Local processes may have strong global impacts when aggregated.

Sudden and drastic changes in broad-scale political, economical, or societal conditions (e.g., revolutions, economic collapse) are overall relatively rare. However, studying land use change in regions where such abrupt changes occur offers unique opportunities to advance understanding of the role of broad-scale factors for land use decisions. Such situations where some broad-scale conditions vary, but other potential land use determinants remain relatively constant may be interpreted as "natural experiments" (*sensu*, Diamond 2001; Geist et al. 2006). This allows for isolating the effect of the varying factors (e.g., institutional change), because observed land use changes can be attributed to the change in broad-scale conditions.

Natural experiments are particularly interesting when comparing the rates and spatial patterns of land use change across borders in environmentally homogeneous regions. Differences in land use change among countries are in such regions likely a result of dissimilar political, socioeconomic, or institutional boundary conditions. Very few studies used these kinds of setups to assess the underlying drivers of land use change. For example, deforestation differed substantially among countries in a Columbian-Ecuadorian border region, likely due to higher colonization pressures and intensification of illegal coca cultivation in Columbia (Vina et al. 2004). Likewise, land use change in the Kenyan part of the Mara ecosystem was more extensive than in the Tanzanian part, due to large-scale agricultural expansion triggered by new market opportunities in Kenya. This resulted in a collapse of the wildebeest population in the Kenyan part of the ecosystem, whereas Tanzanian herds remained largely unaffected (Serneels and Lambin 2001). The few existing studies emphasize the potential of transborder comparisons to better understand the effect of broad-scale factors on land use change. Comparing land use change in border regions where natural experiments occur should therefore give important insights into the role of these factors for land use decisions, however, such comparisons have so far not been carried out.

2 Post-socialist land use change in Eastern Europe

The demise of the Soviet Union following the fall of the Iron Curtain in 1989 resulted in rapid and drastic changes in Eastern Europe's political, societal, and economic structures (Longworth 1997; Turnock 1998b). Democracy was introduced in most former socialist countries, the Warsaw Pact was dissolved in 1991, and far-reaching institutional reforms were issued across Eastern Europe and the former Soviet Union. Centralized planning economies transitioned towards free-market systems, and massive ownership transfers of natural resources and capital assets took place (Swinnen 1997; Mathijs and Swinnen 1998; Sikor 2004). Old markets and trade agreements within the former Socialist Bloc diminished when the Council for Mutual Economic Assistance (COMECON) ceased to exist in 1991. Prices were liberalized, budget constraints were introduced, and new market opportunities were connected to a strong increase in outside competition, both from the West and from other former socialist countries (Turnock 1998b; Trzeciak-Duval 1999). Moreover, the transition period also brought about rapid societal and demographic change, including massive internal and external migration movements, especially of younger population segments (Ioffe and Nefedova 2001; UNESA 2007).

These changes also affected land management policies and institutions, and altered the framework for land use decisions markedly, with an increasing emphasis on economic rather than political influences (Bicik et al. 2001). During socialism, the agricultural sector was reorganized and greatly intensified, which was often based on huge capital investments by the state and subsidies (e.g., guaranteed prices) (Turnock 1998b). This changed drastically after 1990, and the economic transition decreased the profitability of farming considerably, especially in marginal regions. Land management policies were revised and land reforms were carried out to privatize farmland and to individualize land use (Lerman et al. 2004).

Former common pool resources and infrastructure (e.g., irrigation systems) were often neglected and degraded (Penov 2004; Sikor 2004). Altogether, this resulted in widespread land use change in the post-socialist period, most notably the abandonment of vast areas of agricultural land, urbanization, increased logging, and farmland parcelization (i.e. subdivision of large fields into smaller ones) (Peterson and Aunap 1998; Bicik et al. 2001; van Dijk 2003; Lerman et al. 2004; Elbakidze and Angelstam 2007b). Thus, the political and economic transition that occurred in Eastern Europe and the former Soviet Union is a prime example of a large-scale natural experiment that may help to better understand how changes in broad-scale underlying driving factors of land use decisions affect land use change.

Studying post-socialist land use change in Eastern Europe is also important for gathering basic information about the extent of these changes. Concerning land use change, Eastern Europe and the former Soviet Union are clearly an understudied region. Although general land use trends since 1990 are acknowledged, little is known about the rates and spatial patterns of these trends (NEESPI 2004; GLP 2005). This is unfortunate because much is at stake. Eastern Europe still harbors vast areas of relatively wild landscapes with high nature conservation value and some of Europe's last pristine ecosystems (Oszlanyi et al. 2004; Wesolowski 2005). These treasures include wetland areas, for instance the Danube delta, primeval forests (e.g. Bialowieza Forest), the Carpathian mountain forest ecosystems, and the Caucasian mountain range; areas that harbor astonishing biodiversity, including hotspots of global significance (Olson and Dinerstein 1998). Moreover, Eastern Europe and Russia also still have widespread cultural landscapes that have largely been lost in the West (Palang et al. 2006; Elbakidze and Angelstam 2007b).

During socialism, environmental resources were mainly seen as an engine of growth. Great efforts were made to industrialize the agricultural sector and to utilize Eastern Europe's and Russia's natural resources (Csaki 2000; Oldfield 2000). Private landownership ceased, farms were collectivized, and agriculture was intensified considerably. Forests were transformed into farmland, and logging rates were unsustainably high in many areas (Peterson 1995; Csaki and Lerman 1997; Nijnik and Van Kooten 2000; Turnock 2002). Overall, this resulted in considerable environmental problems, many of which persist today (Schrad 2006). The fall of the Iron Curtain in 1989 and the transition from central command economies to free-market conditions reversed some of these trends (Peterson 1995). The decreasing profitability of agriculture resulted in outmigration and farmland abandonment, and human pressure in rural areas has decreased in many areas after 1990. New land management policies considering the multifunctionality of landscapes were issued in many countries, for instance forestry codes promoting sustainable forestry (Kissling-Naf and Bisang 2001). This provides opportunities for biodiversity and nature conservation, and for restoring some ecosystem services that were neglected under high-intensity land use regimes. For example, wildlife populations may benefit from decreasing human pressure in rural landscapes (Stephens et al. 2006), and abandoned farmland offers potential for increased carbon sequestration through afforestation of these lands (Nijnik 2005).

Yet, the transition period was also characterized by weaker institutions, a lower level of control, economic depression, and the infrastructure for nature protection was partially eroded (Sobolev et al. 1995; Wells and Williams 1998). In such situations, environmental conservation may be considerably neglected (GLP 2005) and Eastern Europe and the former Soviet Union have therefore been called “the last frontier for conservation” (Williams 1996; Marcot et al. 1997). Privatization in a period of economic depression may have led to increased resource use, because new owners strived for rapid economic gain (Webster et al. 2001) and economic difficulties in the transition period may have led to increased illegal resource use (e.g., illegal logging, Nijnik and Van Kooten 2000). In some areas human pressure on ecosystems, wildlife, and biodiversity increased considerably since 1990, for example due to poaching, infrastructure development, and oil and gas exploration (Vilchek and Bykova 1992; Forbes 1999; Ervin 2003). As a result, several endemic flagship species have already experienced population collapse, for example saiga antelopes (declined from 1.1 million to 30,000 since 1990, Milner-Gulland et al. 2001), the European bison in the Caucasus (Pucek et al. 2004), and the Siberian tiger (Kerley et al. 2002; Carroll and Miquelle 2006). Also, the persistence of Eastern Europe’s cultural landscapes and the biodiversity they harbor is seriously threatened by outmigration and land use extensification (Cremene et al. 2005; Baur et al. 2006). Overall, recent land use changes may pose both opportunities and serious threats for ecosystems and biodiversity in Eastern Europe. However, the consequences of these changes remain largely unknown.

3 The Carpathian Mountains

The Carpathian mountain range (Figure I-2) represents Europe's largest temperate forest ecosystem and has remained relatively undisturbed compared to Western Europe. The region still harbors a relatively large percentage of natural and semi-natural forests and has exceptionally high levels of biodiversity, including many endangered and endemic species (Webster et al. 2001; Witkowski et al. 2003). For instance, over one-third of all European plant species are found in the Carpathians and much forest biodiversity connected to old-growth stands can still be found in the area (Perzanowski and Szwagrzyk 2001). Being a bridge between Europe's southwestern and southeastern forests, the Carpathians also serve

Figure I-2: Location of the Carpathian Mountains in Europe (altitudes range from approximately 50 to 2,650m, source: Shuttle Radar Topography Mission (SRTM) Digital Elevation Model, ESRI Data and Maps Kit).

as an important refuge and corridor for plants and animals (Webster et al. 2001). Moreover, the region provides habitat for large populations of several top herbivores and carnivores that have been extirpated in wide areas of Western Europe, for example brown bear (*Ursus arctos*), wolf (*Canis lupus*), lynx (*Lynx lynx*), wildcat (*Felis sylvestris*), and European bison (*Bison bonasus*) (Perzanowski and Szwagrzyk 2001; Oszlanyi et al. 2004).

The Carpathians also provide important ecosystem services. For example, the region is an important carbon storage and Carpathian forests are characterized by high productivity (Nijnik and Van Kooten 2000). Carpathian ecosystems are a major source of freshwater and several major rivers (e.g., Vistula, Dnister, Tisza, etc) originate in the region. The potential for recreation and ecotourism of the area is considerable (Webster et al. 2001; Turnock 2002). Moreover, traditional cultural landscapes still widely exist in the Carpathians, whereas they have mostly been lost in the West during the second half of the 20th century. These landscapes, characterized by low-intensity land use, are rich in farmland biodiversity (Donald et al. 2002; Palang et al. 2006; Elbakidze and Angelstam 2007b). However, despite the Carpathian's significance for biodiversity and ecosystem services, surprisingly little is known about their fate in the post-socialist period, and rates and spatial patterns of land use changes in the region remain largely unclear. Moreover, several protected areas were established in the post-socialist period to guard Carpathian ecosystems and biodiversity. Yet, the question remains whether these reserves provided effective protection during a period of political, economic, and societal reorganization.

Despite the urgent need to quantify post-socialist land use change in the Carpathians, the region is also particularly well-suited for carrying out cross-border comparisons of land use change. The region is environmentally relatively homogeneous and constitutes a single ecoregion (Olson et al. 2001; Perzanowski and Szwagrzyk 2001). Moreover, Carpathian countries have a long common history, as the region was a part of the Austro-Hungarian Empire from 1772 until 1918 (Turnock 2002; Augustyn 2004). In this period, land management policies and land use practices were relatively uniform throughout the region. During socialism, most Carpathian countries adopted the general principles of socialist agriculture (e.g., land use intensification, collectivization, state-controlled agricultural sector) (Lerman 2001). Yet, countries also differed markedly in terms of land ownership patterns and land use practices. After the system change in 1989, countries selected different transition strategies (e.g., land reforms) and took different economic and political pathways (Lerman et al. 2004). This provides unique opportunities for assessing the importance of different drivers of land use relative to each other, and for decoupling the effect of overall changes in the post-socialist period (e.g., worsening economic conditions) from country specific transformations (e.g., specific land ownership patterns or land reforms). Comparing post-socialist land use change among Carpathian countries may therefore reveal important insights into how changes in the framework of underlying factors of land use decisions results in land use change. However, no study to date carried out such comparisons among countries in the Carpathians or elsewhere in Eastern Europe.

4 Study Area & Research Questions

The two overarching goals of this thesis are to (I) compare post-socialist land use change across borders in the Carpathian Mountains to better understand the role of politics and socioeconomics for land use change, and (II) to assess the consequences of post-socialist land use change for Carpathian ecosystems.

As a study area, the border triangle of Poland, Slovakia, and Ukraine in the Carpathians was selected, because land ownership and land management in socialist times as well as land reforms after 1990 differed markedly among the three countries (Table I-1). In Poland, collectivization failed and much farmland remained private. However, some areas were forcefully depopulated after border changes between Poland and the Soviet Union in 1947 (Turnock 2002) and these lands were afforested or managed by state-farms (Angelstam et al. 2003; Augustyn 2004). Slovak land owners retained their property rights, but all land was managed by state-controlled cooperatives. In Ukraine, all land was owned and managed by the state (Lerman et al. 2004). After the system change in 1990, the countries also adopted diverse land reform strategies to privatize farmland and to individualize land use. Whereas land was auctioned off in Poland, Slovakia chose to restitute land, and Ukraine distributed agricultural land among the former workers of the collectives (Table I-1).

Table I-1: Land ownership patterns and privatization strategies of the countries in the study area (Source: Lerman et al. 2004, modified).

Country	Land management before 1990	Land ownership before 1990	Privatization strategy after 1990	Farmland available for privatization	Forest land available for privatization	Land market after 1990
Poland	private and state	private and state	sell state land (plots)	all	little	Buy/sell, lease
Slovakia	state	private	restitution (plots)	all	considerable	Buy/sell, lease
Ukraine	state	state	distribution (shares)	all	little	Only lease until 2005

Thus, the study area represents a sample of the three main land ownership and land management systems that existed during socialism (state-owned, collectivized, and private) and includes the three principal land reform strategies adopted after 1990 (selling of land, restitution of land, and distribution of land). This setting provides unique opportunities for better understanding post-socialist land use change and the role of broad-scale driving factors of land use decisions in general. Cross-border comparisons of land use change in the study area are particularly interesting, because the effect of specific ownership patterns and land reforms on land use trends can be separated from land use changes due to general developments in Eastern Europe.

Moreover, the study area is also of exceptional nature conservation value, because it harbors some of the Carpathians least disturbed forests, high biodiversity, and large populations of top carnivores and herbivores (Denisiuk and Stoyko 2000; Perzanowski and Gula 2002). The area is still rich in traditional cultural landscapes (Angelstam et al. 2003; Augustyn 2004). Moreover, the study area contains several protected areas, including the trilateral Eastern Carpathians Biosphere Reserve with zones of increasing human pressure in all three countries (UNESCO 2003). The area is therefore well-suited for assessing how post-socialist land use changes affected Carpathian ecosystems, and for studying the effectiveness of protected areas during a period of political, economic, and institutional change.

Carrying out cross-border comparison of land use change to address the above issues requires separating differences among countries due to socialist land management from those due to land use trends in the transition period. Different starting points for this separation are possible. In this thesis, a two-stage approach starting with contemporary land use is adopted: First, current land use and landscape configuration is quantified to assess differences among countries. Second, rates and spatial pattern of post-socialist land use change is measured to investigate the origin of differences among countries. These two stages translate into two specific central research questions:

<u>Research question I:</u> *Do the Polish, Slovak, and Ukrainian regions of the study area differ in terms of contemporary land use and landscape pattern?*

Quantifying the status quo is the foundation for comparing land use and landscape patterns among countries. The region has relatively homogeneous environmental conditions and a long common history as a part of the Austro-Hungarian Empire with uniform land management policies. Differences among countries are therefore likely a result of land use changes in either the socialist or the post-socialist period (or a combination thereof). Assessing land use change in the post-socialist period alone would overlook differences among countries that already existed at the time of the system change. Such differences are possible in the study area because socialistic land management differed substantially among the countries in the study area (Augustyn and Kozak 1997; Turnock 2002).

<u>Research question II:</u> *What where the changes in land use in the post-socialist period and did land use change differ among the three countries in the study area?*

Assessing the extent and spatial pattern of post-socialist land use change puts today's land cover and landscape pattern among the three countries into the context of historic land management. If countries today differ in terms of land use and landscape pattern, comparing post-socialist land use change among them will reveal whether differences originate in the socialist or post-socialist period. Conversely, if landscapes in the three countries are relatively homogeneous today, quantifying post-socialist land use change will reveal whether this homogeneity is a result of the transition period, or if the countries have always been relatively similar. In other words, this stage assesses the question whether the three countries in the study area are converging or diverging in terms of land cover and landscape pattern since 1990. Moreover, cross-border comparisons of post-socialist land use changes also allows for addressing the fate of Carpathian ecosystems and the effectiveness of protected areas in the study area (the secondary goal of this thesis).

5 Approach & Specific Objectives

Answering the two research questions outlined above is challenging, because conventional datasets such as statistical data, agricultural censuses, cadastre data, or historic maps are of unknown reliability and are often unavailable, particularly from socialist times (Peterson and Aunap 1998; Filer and Hanousek 2002). An alternative is the use of remote sensing. Satellite images have long been a key resource for quantifying rates and spatial patterns of change in the land system (Rindfuss et al. 2004; Lambin and Geist 2006). Images from the Landsat Thematic Mapper (TM) 4 and 5, and the Enhanced Thematic Mapper Plus (ETM+) instruments are particularly well-suited to assess land use change in Eastern Europe, because data from before and after 1990 exist. The sensors have a swath width of 185km, record data at a spatial resolution of 30m and in six spectral bands, have a 16-day repeat cycle, and a continuous data record since 1982 (Goward and Masek 2001; Cohen and Goward 2004). This allows for addressing land use change at the landscape scale with sufficiently high spatial detail to monitor change in Eastern Europe's highly heterogeneous, fine-grain landscapes (Palang et al. 2006).

Satellite image analyses can track changes in land cover, i.e., the biogeophysical characteristics of the Earth's surface. Land use, the purpose for which humans exploit land cover (Lambin et al. 2006), is usually not directly measurable based on remote sensing data. However, in human dominated landscapes and in the absence of natural disturbances, changes in land cover are likely the result of changes in land use. Monitoring changes in land cover and landscape pattern using satellite images may therefore serve as a proxy for land use change and may help to link landscape dynamics to its underlying driving forces (Fox et al. 2002; Rindfuss et al. 2004). The research summarized in this thesis, is based on monitoring changes in land cover and landscape pattern across borders using remote sensing image analysis. This allows for comparing post-socialist land use change among countries and to unravel the effect of land management policies, land ownership patterns, and institutional reforms on land use change.

The main objective relating to *Research Question I* was to

(1) quantify differences in land cover and landscape pattern among the Polish, Slovak, and Ukrainian region of the study area for the year 2000.

Research Question II required three main objectives, each targeted at one specific land use change process in the post-socialist era. These objectives were to

(2) measure post-socialist forest change and to compare forest change among the countries in the study area,

(3) quantify post-socialist farmland abandonment and compare its rates and spatial pattern among countries,

(4) assess changes in land use pattern due to post-socialist land reforms and to investigate whether land use pattern differed among the three countries.

6 Structure of this thesis

This thesis is structured in four main sections (Chapter II-V) that each relate to one of the specific objectives outlined above. In Chapter II, differences in land cover and landscape pattern among the Polish, Slovak, and Ukrainian region of the study area were quantified. This was done using Landsat TM/ETM+ images from 2000 and a hybrid classification approach. The following three sections investigate whether differences among countries can be attributed to socialist or post-socialist land management, thereby answering the question whether countries converged or diverged in post-socialist times. Each of these three sections quantified a specific land use change process based on Landsat TM/ETM+ images from 1986-2000. In Chapter III, differences among countries in the rates and spatial patterns of forest change were assessed, along with a comparison of the effectiveness of protected areas in the study area. This was based on the forest disturbance index (Healey et al. 2005). Chapter IV presents results from the comparison of rates and spatial patterns of farmland abandonment in the study area, based on a support vector machines classification approach. Chapter V summarizes differences in land use patterns among the three countries. This was carried out using multiple regression models that related field size and texture measures from Landsat TM/ETM+ images. Finally, Chapter VI synthesizes the results of the four preceding chapters and provides directions for future research.

Chapters II – V were written as stand-alone manuscripts to be published in international peer-reviewed journals. Each chapter is therefore structured into the subsections background, study area, methods, results, discussion, and conclusions, thereby resulting in a limited amount of recurring material throughout the thesis. The four chapters were published or submitted as follows:

Chapter II: Kuemmerle, T., Radeloff, V.C., Perzanowski, K., and Hostert, P. (2006): Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique, *Remote Sensing of Environment*, 103:449-464

Chapter III: Kuemmerle, T., Hostert, P., Radeloff, V.C., Perzanowski, K, and Kruhlov, I. (2007): Post-socialist forest disturbance in the Carpathian border region of Poland, Slovakia, and Ukraine, *Ecological Applications*, 17:1279–1295

Chapter IV: Kuemmerle, T., Hostert, P., Radeloff, V.C., van der Linden, S., Perzanowski, K, and Kruhlov, I. (2007): Post-socialist farmland abandonment in the Carpathian border region of Poland, Slovakia, and Ukraine, *Global Change Biology*, submitted.

Chapter V: Kuemmerle, T., Hostert, P., St-Louis, V., and Radeloff, V.C. (2007): Using image texture to map field size in Eastern Europe, *Journal of Land Use Science*, submitted.

Two appendices supplement the material shown in Chapters II – VI. Appendix A extends the analyses described in Chapter V by using image texture in a segmentation-based multitemporal classification to map farmland parcelization. Appendix B details a method to correct single-band data distortions in Landsat TM/ETM+ images. Such distortions were frequent in the images used in this thesis and correcting these distortions was essential prior to quantifying land use change (Chapters III-V). Because no ready-to-use correction procedure existed, a correction algorithm was developed within the framework of this thesis. Both appendices were written as independent pieces of research. Appendix A was presented at a conference whereas appendix B was written for publication in a peer-reviewed journal. The references for the appendices are:

Appendix A: Kuemmerle, T., Hostert, P., Schiller, T., and Radeloff, V.C. (2006): Mapping post-socialist parcelization of farmland in Eastern Europe using texture measures. In: Braun, M. (Ed) Proceedings of the 2nd Workshop of the EARSeL Special Interest Group on Remote Sensing of Land-Use & Land-Cover, 28th-20th September 2006, Bonn, Germany.

Appendix B: Kuemmerle, T., Damm, A., and Hostert, P. (2007): A method to detect and correct single-band missing pixels in Landsat TM and ETM+ data, *Computers & Geosciences*, in press

Chapter II:
Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique

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Abstract

Eastern Europe has experienced drastic changes in political and economic conditions following the breakdown of the Soviet Union. Furthermore, these changes often differ among neighboring countries. This offers unique possibilities to assess the relative importance of broad-scale political and socioeconomic factors on land cover and landscape pattern. Our question was how much land cover differed in the Polish, the Slovak, and the Ukrainian Carpathian Mountains and to what extent these differences can be related to dissimilarities in societal, economic, and political conditions. We used a hybrid classification technique, combining advantages from supervised and unsupervised methods, to derive a land cover map from three Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images from 2000. Results showed marked differences in land cover between the three countries. Forest cover and composition was different for the three countries, for example Slovakia and Poland had about 20% more forest cover at higher elevations than Ukraine. Broad-leaved forest dominated in Slovakia while high percentages of conifers were found in Poland and Ukraine. Agriculture was most abundant in Slovakia where the lowest level of agricultural fragmentation was found (22% core area compared to less than 5% in Poland and Ukraine). Post-socialist land change was greatest in Ukraine, were we found high agricultural fragmentation and widespread early-successional shrublands indicating extensive land abandonment. Concerning forests, differences can largely be explained by socialist forest management. The abundance and pattern of arable land and grassland can be explained by two factors: land tenure in socialist times and economic transition since 1990. These results suggest that broad-scale socioeconomic and political factors are of major significance for land cover patterns in Eastern Europe, and possibly elsewhere.

1 Introduction

Humans are the main force behind global conversions of land cover and remote sensing has been a key technology for monitoring this change (Vitousek et al. 1997). To better understand the human dimension of land change it is crucial to link observed changes to their underlying socioeconomic and political causes (Geist and Lambin 2002). Land use decisions are made at a range of nested scales. At the finest scales, individuals make decisions about the use of their land. However, individuals are constrained by broad scale determinants such as land management policies, economic conditions, and societal structures. Land change science has focused on fine scale factors and a number of studies have shown their importance (Geist and Lambin 2002; Linderman et al. 2005). For example, local land use history, individual decision making by land owners, local attitudes, household numbers, and land ownership patterns are all factors affecting land cover change (Dale et al. 1993; Pfaff 1999; Geoghegan et al. 2001; Liu et al. 2003).

Less is known about the effect of broad-scale political and socioeconomic factors on land cover, despite suggestions that they may increasingly override local factors (Lambin et al. 2001). Investigating the relative importance of broad-scale factors is challenging because they cannot be altered experimentally. An alternative approach is to study areas where sudden changes in political and socioeconomic structures occurred, thereby creating "natural experiments" (*sensu* Diamond 2001). Eastern Europe has undergone such a natural experiment following the collapse of the Soviet Union in 1990. The shift from a socialistic planning system to a market oriented economy has resulted in fundamental changes to the political and social institutions as well as economic conditions (Csaki 2000; Bicik et al. 2001). This affected how land use decisions were made, with an increased emphasis on economic rather than political influences (Bicik et al. 2001). In the agricultural sector, the main changes after 1990 have been extensive changes in land ownership and fragmentation of farm fields due to land reforms (Csaki 2000; Sabates-Wheeler 2002). In terms of land cover change, land abandonment is occurring at unprecedented rates, and large areas are converting to grassland and forest (Turnock 1998a; Augustyn 2004; Ioffe et al. 2004). In many Eastern European countries, Estonia (Palang et al. 1998); Czech Republic (Bicik et al. 2001); and Poland (Kozak 2003), to name a few, forest cover increased slightly throughout the 20th century (Augustyn 2004).

Secondary succession and afforestation on marginal arable land have amplified this trend in the post-socialist period (Turnock 1998a; Augustyn 2004).

While general land cover change trends in Eastern Europe are recognized, detailed spatial data on these trends are lacking. In Eastern Europe, conventional data such as maps, agricultural censuses, and statistical data differ in scale and accuracy, making comparisons among countries difficult. Remote sensing can provide land cover information in an efficient, unbiased, and representative way for large areas.

Land cover changes in the post-socialist period have been targeted by few remote sensing studies. In Estonia for example, 30% of agricultural lands used in Soviet times had been abandoned by 1993 (Peterson and Aunap 1998). Changes in village structure were found for an area in southeast Poland and two processes, land abandonment and agricultural intensification, were identified based on a visual assessment of a Landsat image and historic maps (Angelstam et al. 2003). In sub-catchments of the Tisza River in Ukraine, comparison of Global Land Cover Characterization (GLCC) and the Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product showed a 20% increase in forest cover (Dezso et al. 2005). Landsat TM and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data in conjunction with historic maps revealed that forest cover increased up to 40% in the 20th century for a study area in the Western Polish Carpathians (Kozak 2003).

For the socialist period, the intensification of agriculture in mountain valleys and loss in forest cover of up to 9% occurred in Slovakia during the period 1976 to 1992. These trends were derived from the analysis of Coordination of Information on the Environment of the European Union (CORINE) land cover data at a scale of 1:100,000 (Feranec et al. 2003). Similarly, a small study area in Ukraine showed patterns of abandonment of arable land and agricultural intensification for the period from 1966 to 1990 (Poudevigne and Alard 1997).

Thus, although some studies have used remote sensing data to assess land cover change in Eastern Europe, the few existing studies all assess land cover within single countries, often for very small study sites. Comparative meta-analysis of existing studies is impossible due to differences in time periods and methods. No study to date utilizes the natural experiment that occurred in Eastern Europe by comparing land cover or landscape pattern among neighboring countries.

We decided to study the Carpathian Mountains because they are ecologically relatively homogeneous, yet heavily dissected by political borders. Already in socialist times, the Carpathian countries displayed distinct differences in broad-scale socioeconomic factors, for instance in land ownership patterns and land management policies (Turnock 2002). These differences have been magnified since the fall of the Iron Curtain (Mathijs and Swinnen 1998) and make the area ideal for cross-border comparisons. The challenge is to select a classification method that is appropriate in this mountainous region for which relatively little ancillary information is available.

The validity of any comparison of land cover among countries depends on the classification accuracy of the land cover map. For Landsat data, phenology information inherent in multitemporal images improves classification accuracy (Schriever and Congalton 1995; Wolter et al. 1995; Dymond et al. 2002). Using multitemporal imagery however, requires precise georeferencing, because misregistration strongly affects classification accuracy (Townshend et al. 1992). In mountainous terrain, geometric rectification is also necessary to account for relief displacement (Itten and Meyer 1993; Hill and Mehl 2003a). Publicly available topographic maps from Eastern Europe and the former Soviet Union do not provide the degree of accuracy needed for accurate geometric correction. On the other hand, the manual collection of a well distributed set of ground control points (GCPs) is not feasible for large areas, rugged terrain, or where natural ecosystems dominate and identifiable objects are scarce. An alternative is the use of automated methods based on correlation windows that allow for fast collection of large numbers of GCPs (Shlien 1979; Hill and Mehl 2003a).

Supervised classification methods are more effective in identifying complex land cover classes compared to unsupervised approaches, if detailed a-priori knowledge of the study area and good training data exist (Cihlar et al. 1998). The latter is particularly important for studies in Eastern Europe, where traditional and reliable data sources for ground truth such as aerial photographs are often lacking. Similarly, obtaining a good training data set for complex study sites (e.g., with a gradient in elevation) in the field is often challenging (Cihlar et al. 1998). In such situations, unsupervised approaches might be preferable (Bauer et al. 1994; Lark 1995) and they have been rated more robust and repeatable (Cihlar et al. 1998; Wulder et al. 2004).

Ultimately it may be best to combine unsupervised and supervised classification techniques. Three uses of hybrid approaches can be distinguished: first, unsupervised clustering is useful to stratify input images prior to subsequent supervised classifications (Tommervik et al. 2003; Lo and Choi 2004); second, unsupervised methods can reveal spectrally homogeneous areas for optimized training and ground truth collection (McCaffrey and Franklin 1993; Rees and Williams 1997); and third, manually collected training data can be clustered into spectrally homogeneous sub-classes for use in a subsequent supervised classification ('guided clustering'; Bauer et al. 1994, Stuckens et al. 2000). Thus, hybrid approaches bear significant potential to overcome difficulties in delineating appropriate training samples for complex mountainous study areas. However, no standard procedure exists to date and hybrid approaches have to be adjusted to data availability and study area properties. In our study, the challenge was to develop a hybrid approach that yields a consistent land cover map for cross-border comparisons in the Carpathians.

Comparisons of land cover among countries are interesting but can potentially miss differences in landscape pattern. This is important because some processes only become apparent in the configuration of land cover units and not in the abundance of land cover types (e.g., the physical fragmentation of agricultural plots does not necessarily lead to changes in the quantity of arable land). Landscape ecology has focused on developing methods to quantify landscape pattern and fragmentation (Forman and Godron 1986; Turner 1989). However, landscape metrics (e.g., O'Neill et al. 1988a) often do not measure the location of fragmentation and calculate only one aggregate index. This is problematic where fragmentation levels vary. The solution is to use spatially explicit fragmentation measures (Riitters et al. 2002). These methods estimate the local degree of fragmentation, within predefined neighborhoods. Thus, averaging is avoided and patterns of fragmentation may be revealed.

In summary, the Carpathians are an interesting region to study land cover across borders, but land cover classifications that allow the assessment of land cover abundances and landscape pattern may not be trivial. The overarching objective of our project was to investigate whether there are distinct differences in land cover and landscape patterns between portions of three neighboring countries in the Carpathian Mountains (Poland, Slovakia and Ukraine) for the year 2000. Our specific aims were:

(1) To derive a consistent land cover map from multitemporal Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data for cross-border comparisons and to develop and test a hybrid classification method to overcome

difficulties in delineating appropriate training samples for complex mountainous study areas.

(2) To compare landscapes across borders based on land cover abundances, landscape metrics, and spatially explicit fragmentation measures adopted from Riitters et al. (2002).

2 Study area

We studied the border triangle of Poland, Slovakia, and Ukraine. The area was part of the Austro – Hungarian Empire for about 150 years until 1918 and during this period, political institutions and land management policies were homogeneous. Since World War II, the region has been subject to fundamental changes in political and socioeconomic systems, which in turn affected population density and land use practices (Turnock 2002; Augustyn 2004). These changes differ among countries. For example, population density in Ukraine and Slovakia has increased while some areas in the Polish region of the study area were depopulated after 1947 following border changes between the Soviet Union and Poland (Turnock 2002). As a result, large areas in Poland were converted to forests (Augustyn 2004). Agricultural land in Slovakia and Ukraine was almost completely collectivized, while in the Polish region a large fraction of farmland remained in private ownership. Since 1990, the speed and intensity of the economic transition has differed among the three countries. This is mainly due to dissimilar starting points as well as the integration of Poland and Slovakia into the European Union (Csaki 2000; Turnock 2002).

The study area (Figure II-1) is centered on the border triangle. Boundaries were based on the extent of the Landsat TM scene, landscape features such as rivers and valleys as well as administrative borders. The study area encompasses 17,800km² and is characterized by mountainous topography with altitudes ranging from 200 to over 1,300m above sea level. The climate is moderately cool and humid with marked continental influence and an annual mean temperature of 5.9°C (at 300m). The average annual precipitation is between 1,100 and 1,200mm (Augustyn 2004). Although a variation in the amount of precipitation along the altitudinal gradient may exist, it has not been reported. The uniform bedrock is composed of Carpathian flysh, consisting of sandstone and shale (Denisiuk and Stoyko 2000; Augustyn 2004). Climate, topography, and anthropogenic factors produce complex vegetation patterns including broad-leaved forests dominated by beech (*Fagus sylvatica*) and sycamore (*Acer pseudoplatanus*), mixed forests with beech and fir (*Abies alba*), coniferous forests composed of fir, Norway spruce (*Picea abies*), and Scots Pine (*Pinus sylvestris*), mountain meadows, grasslands, and arable land (Denisiuk and Stoyko 2000). Specific for the Eastern Carpathians are mountain meadows, so-called *poloniny*, which are found at higher altitudes and on hilltops (Denisiuk and Stoyko 2000). Although the area is environmentally relatively homogeneous (UNESCO 2003), climate variations between the northern and the southern rim affect forest composition (Denisiuk and Stoyko 2000). For instance beech/fir forests are a natural vegetation formation on north-facing slopes, while beech forests would dominate south-facing slopes without anthropogenic influence.

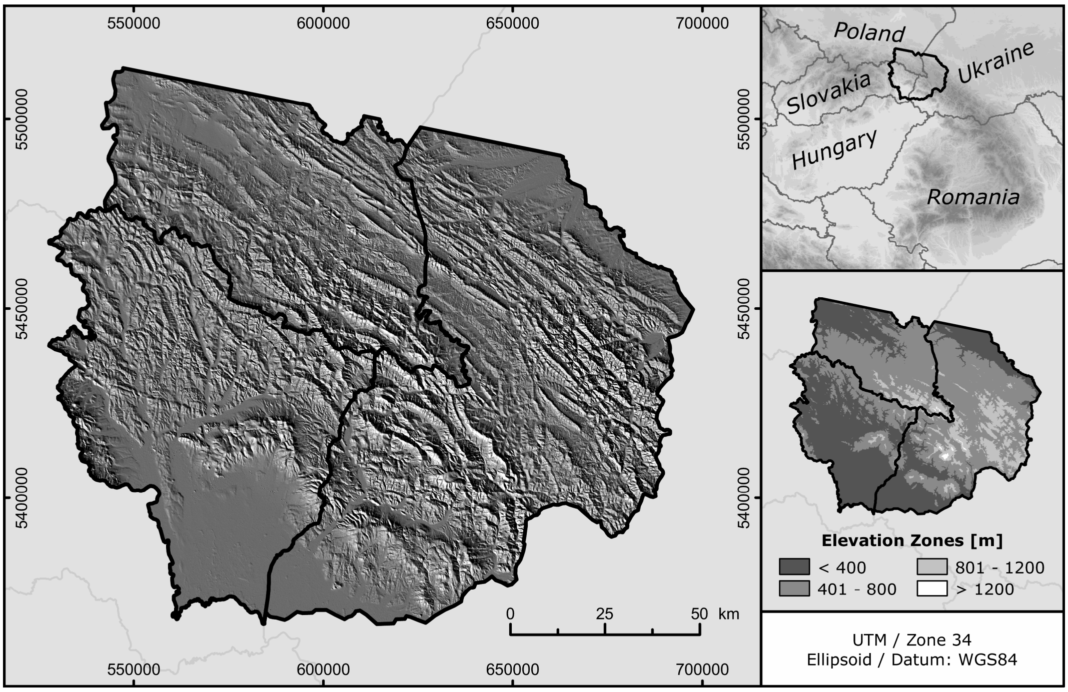


Figure II-1: The border triangle of Poland, Slovakia and Ukraine, located in the north-eastern part of the Carpathian ridge (shaded SRTM relief).

3 Data and Methods

3.1 Satellite and field data

Three images from path 186, row 26 were acquired for the year 2000 (ETM+ for 2000-06-10, TM for 2000-08-21, and ETM+ for 2000-09-30). The thermal bands were not retained for the analysis because of their lower spatial resolution and the weaker signal to noise ratio. The 3 arc second Space Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) was acquired from Aeronautics and Space Administration (NASA) and resampled using bilinear interpolation to match the spatial resolution of the Landsat data.

Ground truth data to be used in the assessment of classification accuracy was gathered in the field in the summer of 2004 and spring of 2005. Plots were mapped for all 10 land cover classes (compare Table II-1) in areas with good accessibility (i.e., close to roads and trails) using non-differential Global Positioning System (GPS) receivers. Inaccessible areas were photo-documented, the area covered by the pictures was located in the imagery and ground truth points were digitized on screen. Additional ground truth plots were collected from ancillary dataset sources. Three Quickbird images (2003-05-07) were available for the Ukrainian region of the study area. For a portion of the study area in Poland, forest inventory maps and stand statistics were made available by the Polish Forest Administration. These maps were produced between 1995 and 1999 and provide a wide variety of information including stand age and composition. Care was taken to gather ground truth data only for locally homogenous sites (i.e., 90x90m or 3x3 Landsat TM pixels) to rule out erroneous assignments due to positional uncertainty.

Categorization of ground truth plots for mixed forest classes (e.g., to distinguish broad-leaved, mixed, and coniferous forest) was guided by the forestry inventory information.. Mixed forest was defined as not having a dominating fraction (i.e., more than 70%) of broad-leaved or coniferous species. Shrubs and secondary succession stands were categorized visually into two classes (sparse shrub cover and medium to dense shrub cover) using a threshold of about 15% shrub cover. Only plots with medium to dense shrub cover were classified as shrublands. Areas with sparse shrub cover (i.e., early stages of secondary succession) were labeled as grasslands. Due to the time span between image acquisition (2000) and field campaigns (2004-05), sparse shrub cover likely evolved after the recording of the Landsat images. In total, 1,477 control points (905 based on ground visits and 572 from additional datasets) were used in the accuracy assessment.

To facilitate class labeling and training data collection in the classification process, 3 sites in Poland and 2 sites in Slovakia were mapped extensively, in addition to the ground truth data mentioned above. The sites covered a total of 124km² and were chosen to represent characteristic landscapes of the study area. Mapping was carried out using non-differential GPS units and handheld computers. For the Ukrainian region of the study area, training sites mapped in summer 2000 were available from a previous project (BMBF 2005).

3.2 Preprocessing of Landsat data

Precise georeferencing and correction of geometric distortions, requires a set of high quality ground control points (GCPs). To ensure high positional accuracy, we used an automated search algorithm to delineate large numbers of GCPs (Hill and Mehl 2003a). This method requires a rough manual co-registration of the base map and raw image with a limited number (< 10) of control points. Locations of potential GCPs are derived using a systematic sampling technique (e.g., a grid with a mesh size of 100 pixels). The quality of each potential GCP in this grid is evaluated based on correlation windows. A correlation coefficient is calculated between the spectral values of corresponding subsets in the base map and the uncorrected image. First, a small window (e.g., 10x10 pixels) is centered on a potential GCP in the base map. This window is correlated with all equally sized windows within a user-specified neighborhood around the approximate location of the corresponding point in the unregistered image. A correlation coefficient is calculated for each pixel in the neighborhood of a potential GCP, resulting in a plane of correlation coefficients. The peak in that plane indicates good agreement between the potential GCP location in the base map and the location of the peaking pixel in the unregistered image (Hill and Mehl 2003a) (Figure II-2).

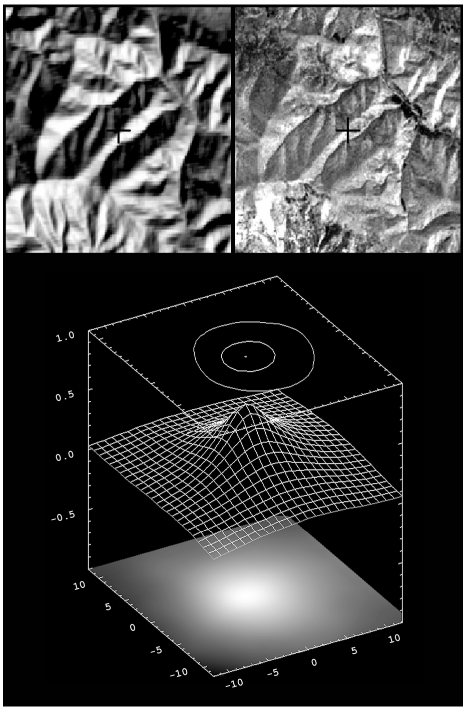


Figure II-2: Top: Corresponding windows of the base map (shaded SRTM DEM) and raw image (ETM+ band 4) centered on a potential GCP. Bottom: Visualization of a plane of correlation coefficients calculated by correlating a 10x10 pixel-wide window centered on a potential GCP in the base map with all 10x10 sized windows within the subset of the raw image. A good GCP is represented by a high peak in the plane of correlation coefficients (x,y-axes: pixel position, z-axis: R).

We georectified the June ETM+ image using the referenced SRTM DEM as the base map due to the lack of freely available detailed topographic maps for the area. A shaded topographic image was derived from the DEM using sun azimuth and elevation from the

June ETM+ image. To ensure the best possible agreement of the topographic model and the Landsat imagery, we also added the parallax error (i.e., off-nadir relief displacement due to local terrain elevation) to the DEM. Correlating the resulting topography model with the near infrared band (band 4) yielded the best results, presumably because it displays strong topographically induced illumination differences while having a high signal to noise ratio. The resulting large number of potential GCPs (>500) was screened based on individual error contribution as well as spatial and altitudinal distribution and suboptimal points were dismissed. The June image was rectified to the Universal Transverse Mercator (UTM) coordinate system and the World Geodetic System 1984 (WGS84) datum and ellipsoid using collinearity equations and considering elevation information to accommodate for relief displacement. The August and September images were registered to the June image based on a correlation of the near infrared bands using the same procedure. Overall root mean square errors (RMSE) of all GCPs were 0.16, 0.24, and 0.24 pixels for the June, August and September images respectively. Comparison with field data (control points and road tracks mapped via GPS) confirmed high positional accuracy.

Atmospheric correction and topographic normalization can improve classification results (Song et al. 2001; Hale and Rock 2003). The latter is particularly important for mountainous areas and multitemporal data, because spatial variations in illumination and radiance can cause identical surfaces to reflect differently (Itten and Meyer 1993). Correcting topographic and atmospheric influence concurrently can avoid overcorrection common to simple topographic normalizations such as the cosine-correction (Hill et al. 1995; Richter 1998). Also, the global flux for non-planar pixels can be precisely calculated, because topographic-induced differences in surface reflectance are taken into account (Hill et al. 1995). We applied a two-stage absolute atmospheric correction. First, at-satellite radiance was calculated using TM calibration gains (Chander et al. 2004) and biases (Markham and Barker 1986). The ETM+ data was processed using reported calibration constants (USGS 2006). Second, at-sensor radiance was converted to target reflectance using radiative transfer modeling (Tanre et al. 1990). We used a modified 5S-Code that incorporates a terrain dependent illumination correction (Hill and Sturm 1991; Radeloff et al. 1997; Hill and Mehl 2003a). To prevent overcorrection in areas of low illumination (because Lambertian reflectance is assumed for non-Lambertian surfaces such as vegetation), the Minnaert constant (e.g., Itten and Meyer 1993; Ekstrand 1996) was set to 0.75 for the late summer and autumn image. Comparison of neighboring spectra from shaded and unshaded hillsides and a visual assessment showed that topographic distortions were effectively removed without causing overcorrection (Figure II-3).

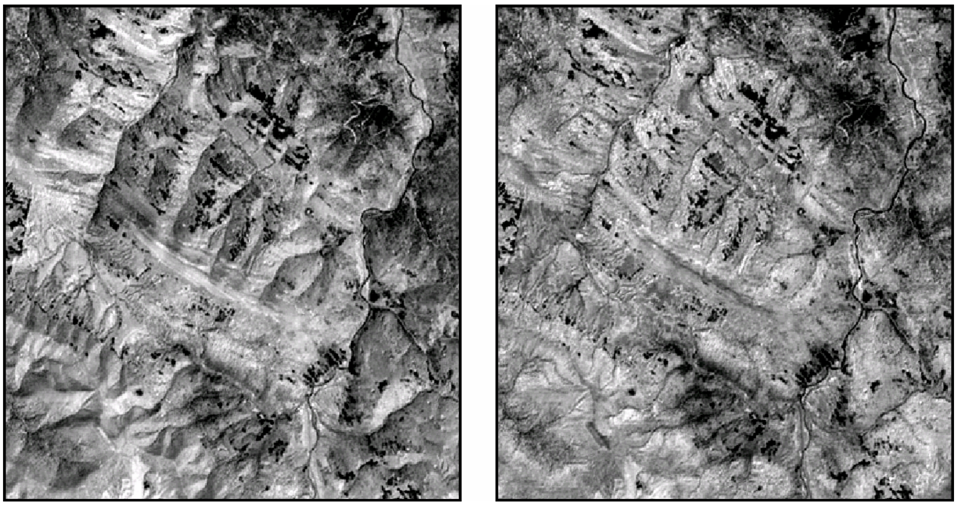
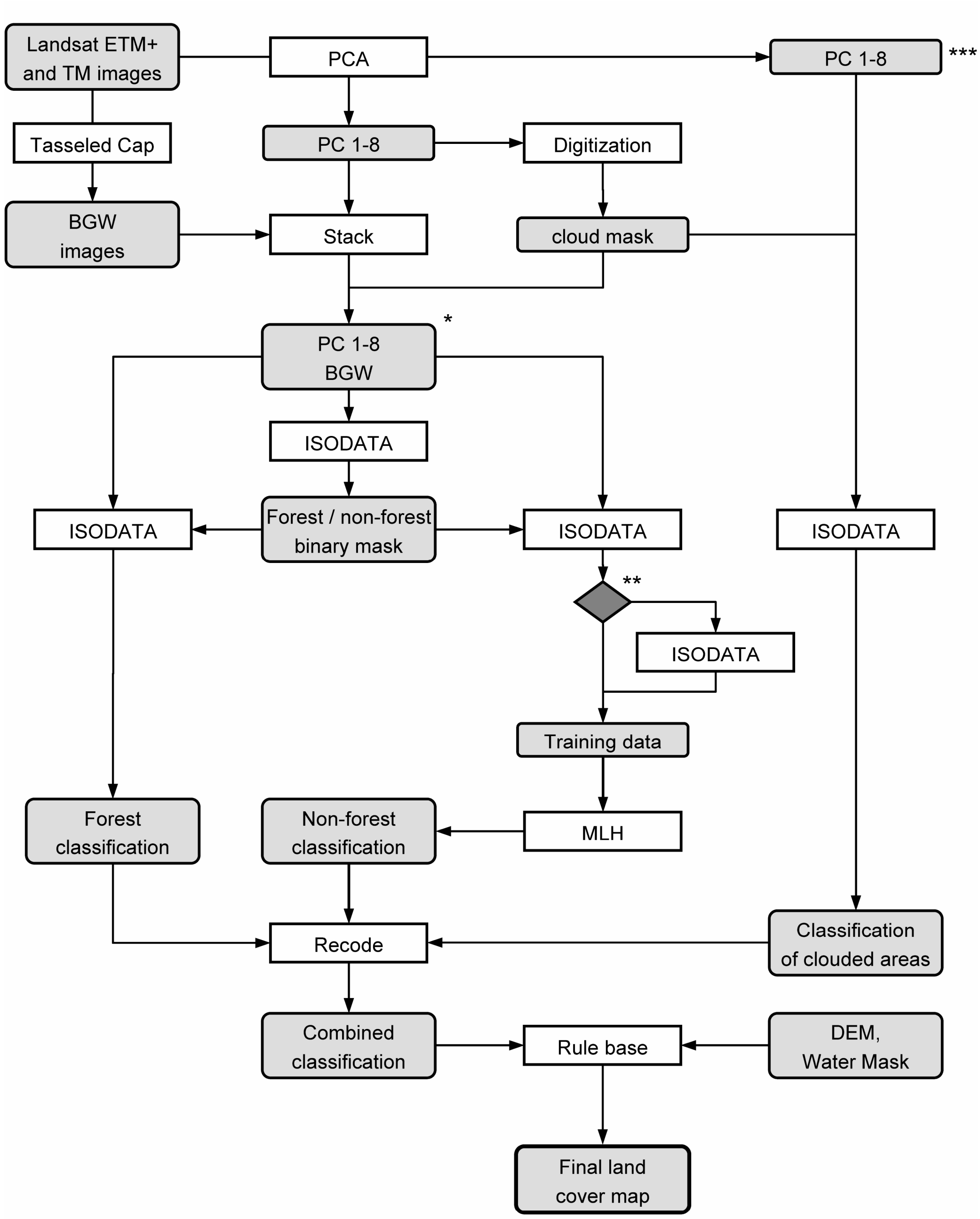


Figure II-3: First principal component from 2000-06-10 before (left) and after (right) radiometric rectification and topographic correction.

The stack of all three images was transformed into principal components (PCs) to enhance signal to noise ratio and to reduce data volume. Typically, the first three principal components account for most of the variation in the data. In our case, PC 4 to 8 proved to be valuable because phenological differences between the three images fell into these components and phenology differences between arable land and grassland were important to separate theses classes. PCs 4 to 8 also contained significant amounts of variance based on eigenvalue analysis. Together, PCs 1 to 8 accounted for 98% of the variance in the stack of all three images. In addition, we computed Tasseled Cap images for each phenological period (Crist and Cicone 1984) because brightness, greenness, and wetness (BGW) bands capture phenological differences and can enhance classification results (Oetter et al. 2001; Dymond et al. 2002).

3.3 Classification

To combine the benefits of supervised and unsupervised approaches, we used a hybrid classification (Figure II-4) to derive 10 land cover classes (Table II-1). PC bands 1 to 8 and the BGW bands of the individual images were used as input. Initially, we conducted an unsupervised Iterative Self-Organizing Data Analysis (ISODATA) clustering into 40 clusters to separate forest and non-forest. Hyperclustering, i.e., using a much higher number of clusters than classes (Bauer et al. 1994) was chosen because the exact number of spectral classes in the data set was unknown (Cihlar 2000). The potential difficulty with hyperclustering lies in small spectral classes that may be hard to label (Cihlar 2000). Initial tests showed that 40 classes could adequately distinguish forest from non-forest while still being interpretable. Subsequently, forested areas were clustered again into 40 classes and labeled as broadleaf, mixed, and coniferous forest based on field data and forestry maps.



* Stack of principal components 1 to 8 and the BGW of the three individual dates
** Class evaluation using on-the-fly classification of training sites, feature space images, class dendrogramms
*** Only data from non-clouded dates

Figure II-4: Classification scheme (for details compare to text; MLH = maximum likelihood classification, PCA = principal component analysis).

For the non-forested pixels, clustering techniques alone proved to be inadequate. Instead, a two stage combination of unsupervised and supervised methods was used. First, we conducted unsupervised hyperclustering to minimize bias in the selection of training areas and seed signatures. Eighty classes proved to be a good compromise between spectral pureness and interpretability. Class signatures were examined using feature space images and dendrograms depicting hierarchical relations between classes. On-the-fly parallelepiped classification was used to evaluate spectral pureness of classes. Unambiguous signatures were retained, small classes were deleted, and spectrally similar classes of identical land cover type were merged. Ambivalent classes were masked out and further sub-clustered (using 10-25 sub-classes) to obtain unambiguous signatures for all land cover types. The comprehensive set of spectral class signatures was used in the second stage as training data for a maximum likelihood (MLH) classification. In an iterative procedure, the signature set was refined and additional signatures were gathered manually for areas where misclassifications occurred and Mahalanobis distances to existing cluster means were high.

Table II-1: Class scheme, class descriptions, classification method and training data for the hybrid classification (* H = hybrid classification; C = ISODATA clustering; KB = knowledge-based; **number of clusters)

Classes	Acronym	Description	Classification approach	# training signatures
Water	W	Open water, rivers and lakes	H	1
Dense settlements	DS	Dense built up areas, cities, construction areas	H	9
Open settlements	OS	Suburbs, villages, small gardens and orchards	H	6
Broad-leaved forest	BF	Minimum fraction of broad-leaved trees of 70%	C	24**
Mixed forest	MF	Neither broad-leaved nor coniferous species dominate	C	8**
Coniferous forest	CF	Minimum fraction of coniferous trees of 70%	C	7**
Shrubland	SH	Secondary succession on fallow land, early reforestation and heath lands	H	19
Grassland	GR	Pastures, meadows and unmanaged grasslands	H	32
Poloniny	PO	High mountain grasslands	KB	---
Arable land	AL	Agricultural areas	H	58

The autumn image (2000-09-30) included 3 clouds (~ 3% of the study area). Clouded areas and their corresponding cloud shadows were digitized manually. These areas were classified separately using only data from the remaining, cloud-free images. Because the affected area was small and contained dominantly forest classes, unsupervised ISODATA clustering with 40 classes proved to be adequate. A 300m buffer around the clouds was established and class labeling was carried out in comparison with the classification product of cloud free areas to ensure consistency.

A post-classification step allowed separation of the mountain meadows (*poloniny*) class and improved the classification of water. The *poloniny* class was spectrally not separable and classified using an elevation threshold of 1,030m. The shallow creeks and rivers of the study site lead to confusion with the coniferous forest class. The class was improved by deriving water pixels based on thresholds for PCs 1 and 2.

The land cover map was stratified into elevation zones to enable the assessment of land cover across borders. Comparisons of land cover were based on relative proportions within single elevation zones, to avoid potential biases introduced by the selection of study area boundaries (Figure II-1).

3.4 Landscape structure

Post-socialist land reforms and land abandonment were expected to have an effect on landscape pattern and landscape fragmentation. These processes were not assumed to occur uniformly along an altitudinal gradient. For example, land abandonment was expected to occur on marginal land that is more frequently found at higher altitudes. We calculated the average size of each land cover patch and its mean elevation. To assess the relationship of these two variables, we derived two-dimensional density distributions using an axis-aligned bivariate normal kernel (Venables and D. 2002). This was done for the land cover types arable land, grassland, and shrubland, because land reforms were assumed to exert influence on the patch sizes of these cover types. Density distribution did not prove useful to assess forest cover, because forest patches are very large in the region resulting in a relatively small number of patches. To exclude micro-patches from the analysis, the land cover map was majority filtered using a 3x3 operator prior to the calculations of patch metrics.

Fragmentation of the land cover classes arable land, grassland, and total forest were further assessed in a spatially explicit way using fragmentation indices proposed by (Riitters et al. 2002). These indices are based on two measures, land cover proportion (PLC) and land cover connectivity (CLC), and were calculated around each pixel. PLC is the percentage of the target land cover class in the neighborhood. To calculate CLC, we first determined the number of true edges (edges between pixels of the target land cover type and other land cover types, e.g., forest-non-forest edges) and the number of interior edges (edges between pixels of the target land cover type, e.g., forest-forest edges) of a neighborhood based on the grey level co-occurrence matrix. CLC is the sum of interior edges divided by the sum of true edges and interior edges. Thus, CLC is an approximation of the probability that a land cover pixel is located next to a pixel of the same land cover and high values of CLC indicate a higher degree of land cover connectivity (Riitters et al. 2002). Two differently sized neighborhoods, 2.25ha (5x5 pixels) and 7.29ha (9x9 pixels) were applied for the land cover classes arable land and grassland. For forest cover, an additional scale of 65.61ha (27x27 pixels) was included to accommodate for bigger patch sizes of this land cover type.

PLC was categorized into four classes for each scale to enable comparison between countries: core (PLC = 1), interior (1 > PLC > 0.9), dominant (0.9 ≥ PLC > 0.6), and intermediate (0.6 ≥ PLC > 0.4). To analyze the location of fragmentation, a rule-base was adapted to assign each pixel to one of four components of fragmentation (Riitters et al. 2002). “Core” is equivalent to the core component of PLC and “patch” represents the dominant and intermediate classes of PLC. Where PLC was between 0.6 and 1, a pixel was labeled “perforated” for PLC > CLC and labeled “edge” for PLC ≤ CLC. This implies that the configuration of land cover units is compact for the perforated class while the edge class is characterized by a disconnected pattern (Riitters et al. 2002).

4 Results and Discussion

4.1 Land cover classification

The land cover classification showed that the majority of the slopes of the Carpathian ridge were forested (Figure II-5). In the mountain valleys, a patchwork of grassland and agriculture was observed at intermediate altitudes while at higher altitudes grasslands prevailed. The lower areas in the southern, northwestern and northeastern regions of the study area were dominated by arable land.

The hybrid classification approach performed well and resulted in a reliable land cover map for cross-border comparisons with an overall classification accuracy of 84% and an adjusted kappa of 0.80. Broad-leaved forest, coniferous forest, and *poloniny*, had users and producers accuracy of more than 90% (Table II-2). Multitemporal imagery and Tasseled Cap transformations separated arable land and grassland well considering the degree of spectral collinearity of some spectral sub-classes. The unsupervised clustering prior to the maximum likelihood classification was helpful in identifying spectral classes and reducing bias in the collection of training data.

The land cover classes open settlements, mixed forest, and shrublands show accuracies of less than 80% (Table II-2). Generally, the classification of mixed classes may be problematic, because class borders are drawn artificially (Schriever and Congalton 1995; Foody 2002), and often there is an underlying conflict regarding the desired thematic classes and their spectral separability. Shrublands proved particularly difficult to classify because of their overlap with grassland and the high degree of spectral heterogeneity. For instance, the composition of shrublands ranges from encroaching alder (*Alnus spec.*), hawthorn (*Crataegus spec.*), or pine (*Pinus spec.*) shrubs on meadows in Poland, to juniper (*Juniperus communis*) heath communities in Ukraine.

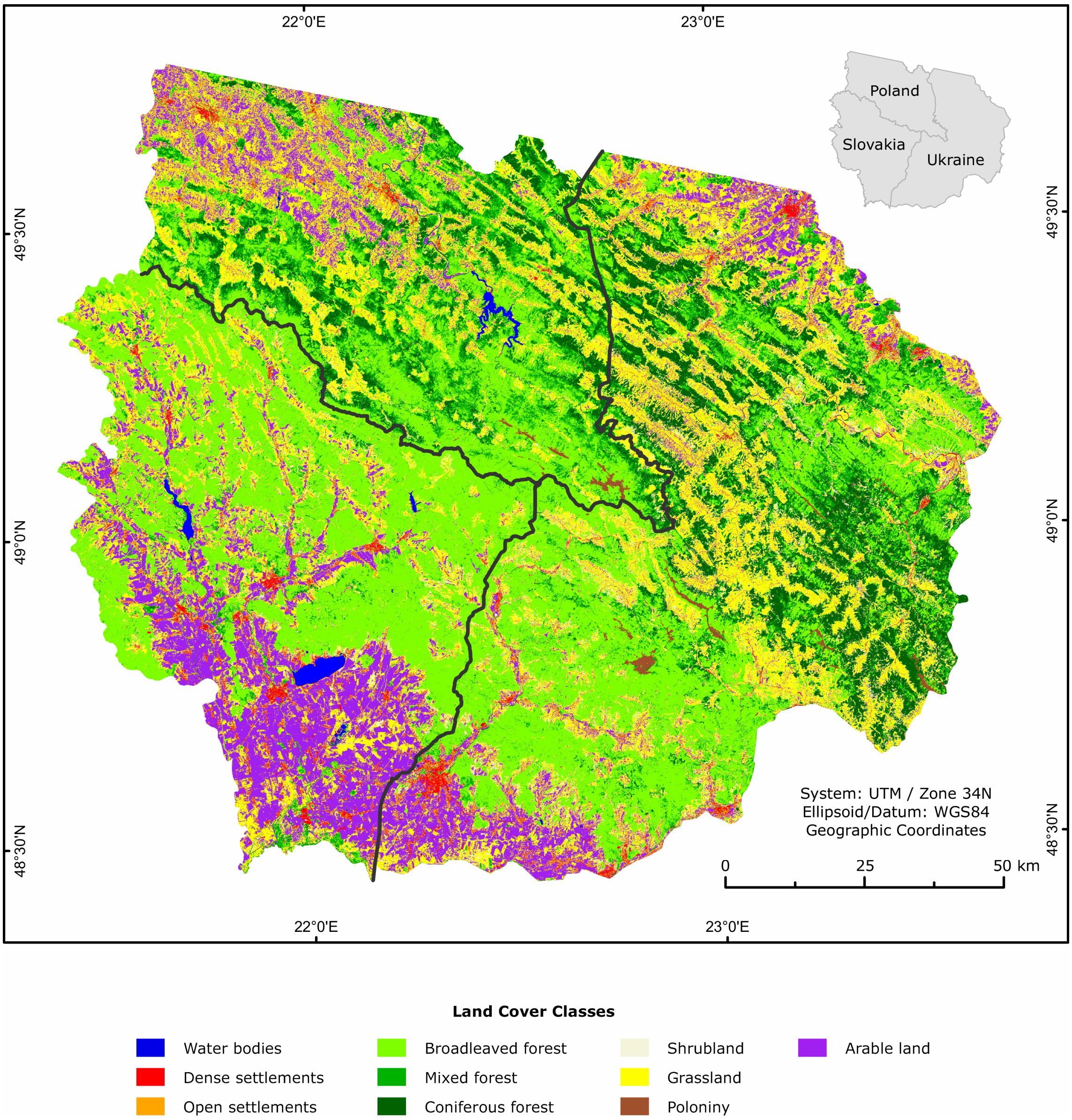


Figure II-5: Land cover map for the border triangle Poland, Slovakia, and Ukraine

Accuracy assessment is most reliable when using a random sample of ground truth points (Congalton 1991) but obtaining such a data set is not always feasible (Foody 2002). In our case, inaccessibility of some areas, rugged terrain and other practical restrictions inhibited the manual collection of a randomly distributed set of points. The set of ground control points used in this study was carefully selected to be independent from the training data, to cover a wide area, different altitudinal zones and to represent the spectral sub-classes of the land cover types, but we cannot completely rule out a bias. However, we suggest that any potential bias is distributed evenly throughout the study area, and would not have affected our country comparisons.

Table II-2: Confusion matrix for the hybrid classification (UAC = user's accuracy, PAC = producer's accuracy, CKA = conditional kappa; acronyms are explained in Table 1)

		Reference data											
		W	*DS*	*OS*	*BF*	*MF*	*CF*	*SH*	*GR*	*PO*	*AL*	*∑*	*UAC*
Classified data	W	**23**	0	0	0	0	0	0	0	0	0	23	1.00
	DS	1	**45**	5	0	0	0	0	0	0	1	52	0.87
	OS	1	7	**55**	0	1	0	2	1	0	3	70	0.79
	BF	0	0	0	**233**	12	1	7	8	1	2	264	0.88
	MF	1	0	0	9	**45**	15	1	0	0	0	71	0.63
	CF	4	0	0	0	10	**142**	1	0	0	0	157	0.90
	SH	1	0	1	0	1	0	**51**	23	0	3	80	0.64
	GR	0	0	6	3	0	0	33	**378**	0	43	463	0.82
	PO	0	0	0	0	0	0	0	0	**19**	0	19	1.00
	AL	0	1	7	0	0	0	2	21	0	**247**	278	0.89
	∑	31	53	74	245	69	158	97	431	20	299	1,477	
	PAC	0.74	0.85	0.74	0.95	0.65	0.90	0.53	0.88	0.95	0.83		
	CKA	1.00	0.86	0.77	0.86	0.62	0.89	0.61	0.74	1.00	0.86		

4.2 Cross-border comparison of land cover and landscape pattern

The border area of Poland, Slovakia, and Ukraine is environmentally fairly homogeneous yet the comparison of land cover revealed marked differences in land cover proportions and landscape pattern among these countries. We suggest that these differences at least partially reflect differences in the socioeconomic conditions, both currently and in the past. From 1772 until 1918 the area belonged to one country (the Austro-Hungarian Empire) (Augustyn 2004). This suggests that differences in land cover are largely a result of changes during socialist and post-socialist times.

Forests

Forest cover and forest composition differed most strongly among the three countries. In mountainous areas, forest cover was much lower in Ukraine compared to Poland and Slovakia. For instance at elevations of 400-800m, forest cover was 84% in Slovakia, but only 61% in Ukraine (Figure II-6). Concerning forest composition, the main difference was the dominance of broad-leaved forest in Slovakia while coniferous and mixed forests were more abundant in Poland and Ukraine (Figure II-6). Differences were again most

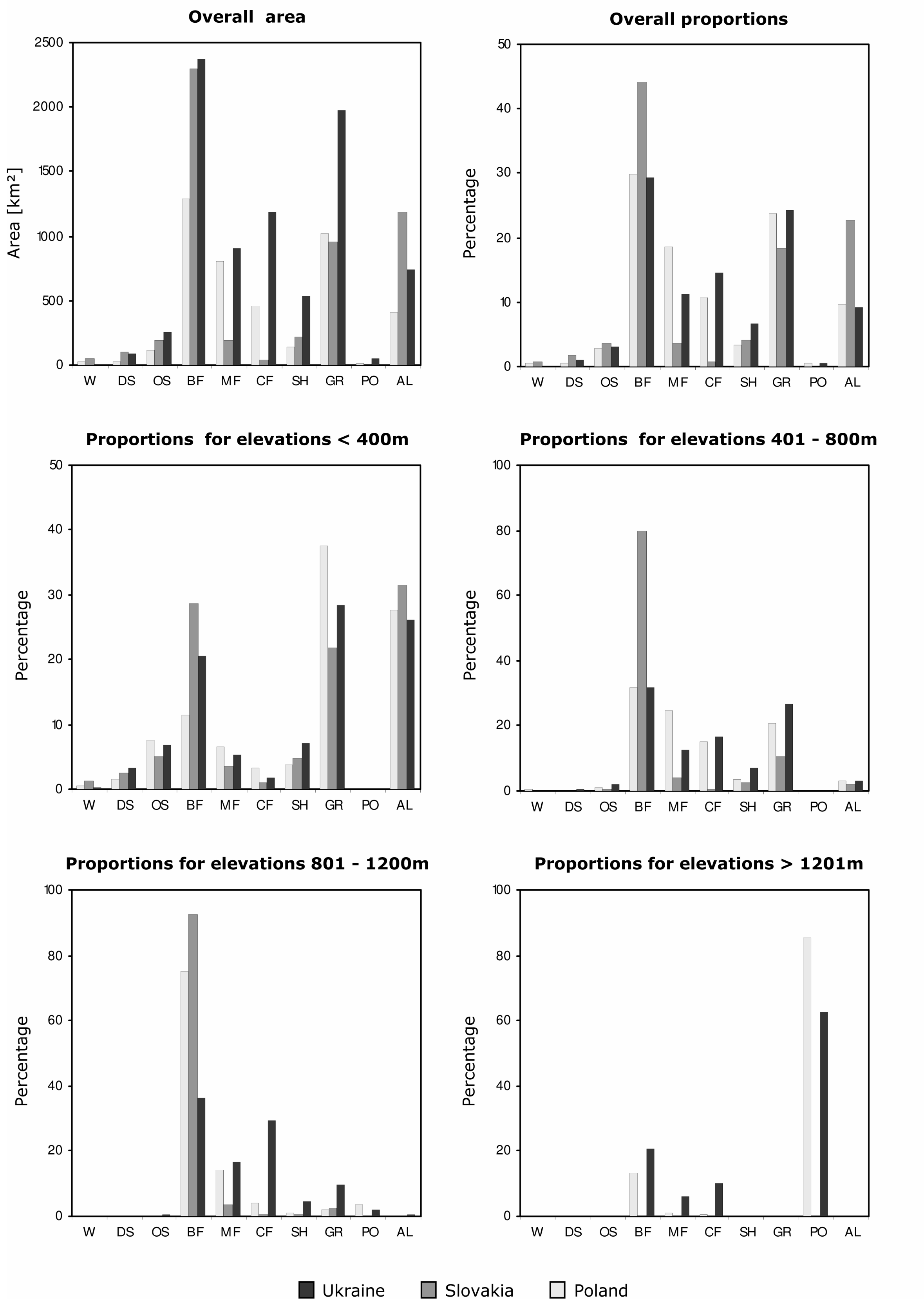


Figure II-6: Comparison of land cover between the three countries. Top left: absolute area; Top right: proportion of land cover normalized by the total area of each country. Middle and bottom: proportions of land cover classes per altitudinal zone (acronyms are explained in Table II-1).

prominent at higher elevations, where Slovakia had up to 48% more broad-leaved forest than the other countries, and Ukraine had striking percentages of conifers (Figures 6, 7). Natural vegetation in the study area is beech (*F. sylvatica*) forest on the southern slopes and mixed beech and fir (*A. alba*) forest on the northern rim (Denisiuk and Stoyko 2000). Although there are differences in forest composition between north and south slopes, we suggest that the observed differences in forest composition are largely anthropogenic in origin. Particularly, pure coniferous forests that we found in Poland and Ukraine (Figure II-5) do not occur naturally in the area. These differences are most likely a legacy of socialist forest management practices and policies, because almost all forests were harvested at least once in the 20th century and the vast majority of forests were mature in 1990 (Turnock 2002).

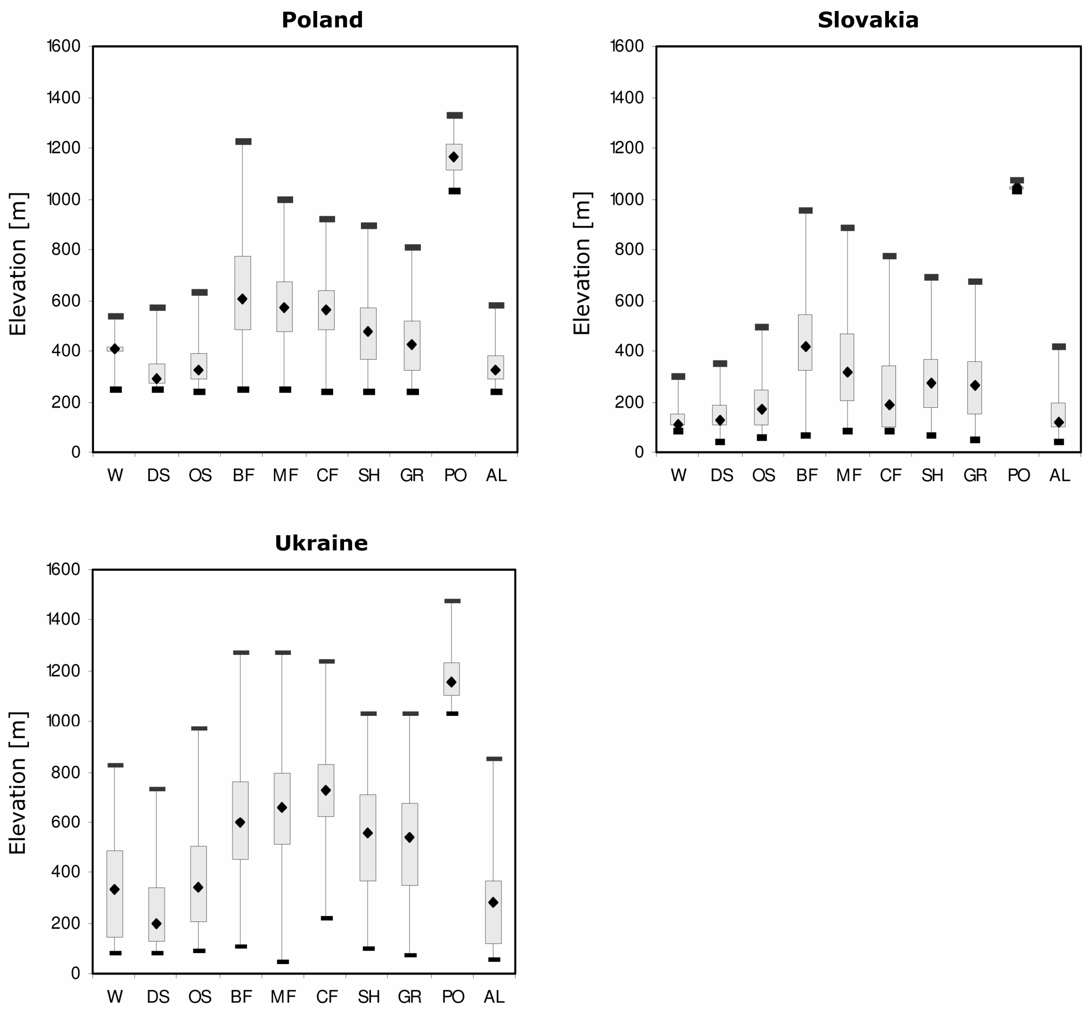


Figure II-7: Boxplot graphs of the distribution of elevation for each class and country (◆ represent class medians; box determines the first and third quartile; whiskers represent upper and lower range, max/min values exceeding the range of ± 3 standard deviations (STD) were treated as outliers and the 3STD limit was taken instead; acronyms are explained in Table II-1).

In Poland, forest cover was significantly lower before World War II than it is today (Turnock 2002). Following border changes between Poland and the Soviet Union, large areas of the Eastern Polish Carpathians were depopulated between 1945 and 1947 causing widespread afforestation with conifers (mainly spruce) and natural succession (Turnock 2002; Augustyn 2004). This resulted in considerable amounts of coniferous and mixed forests at lower altitudes (Figure II-6), especially on sites close to the lower tree line in the valleys (Figure II-5). Afforestation following the forced resettlement is also a likely explanation of the unique altitudinal distribution of forest types found in Poland, where coniferous forests were on average found in lower elevations compared to other forest types (Figure II-7). Since the 1970s, Poland changed its forest policy for the Eastern Carpathian area from clear cutting to selective harvesting and broad-leaved forest was no longer replaced by coniferous forest (Turnock 2002). The reported increase in forest cover after 1947 in conjunction with the low population density explains the lowest level of forest fragmentation (Figure II-8) and the higher amount of core forest areas we found in Poland (Table II-3).

Slovakia's forest composition is dominated by deciduous forests, particularly at altitudes above 400m, and thus is closer to natural vegetation than forests in Poland and Ukraine (Figure II-6). Yet, forests in Slovakia are highly managed and clear cutting was widespread in socialist times and continues today (Feranec et al. 2003). As a result, we found forest fragmentation to be highest in Slovakia. Slovak forest harvesting is often conducted in very narrow strips. Although small clear cuts were common, the narrowest strips may not exceed the width of a Landsat TM or ETM+ pixel (30 meters), and thus may be difficult to detect. Therefore the level of forest fragmentation in Slovakia may be even higher than indicated in our findings.

In Ukraine, lower forest cover, the high proportion of coniferous (Figure II-6) forest, and the high forest fragmentation (Figure II-8) can be explained by three processes. First, Ukrainian forests were overexploited in Soviet times (Turnock 2002) and natural forests were replaced with fast-growing conifers, particularly at higher elevations (Figure II-7). While this was most extensive on northern slopes, former clear cuts are also found on southern slopes, and these clear cuts are now occupied by successional shrublands or mixed forest. Second, population density is relatively high in Ukrainian mountain valleys (UNESCO 2003) thus forests are generally only found on sites unsuitable for agriculture and generally at higher altitudes than in the other countries. Third, Ukrainian forest

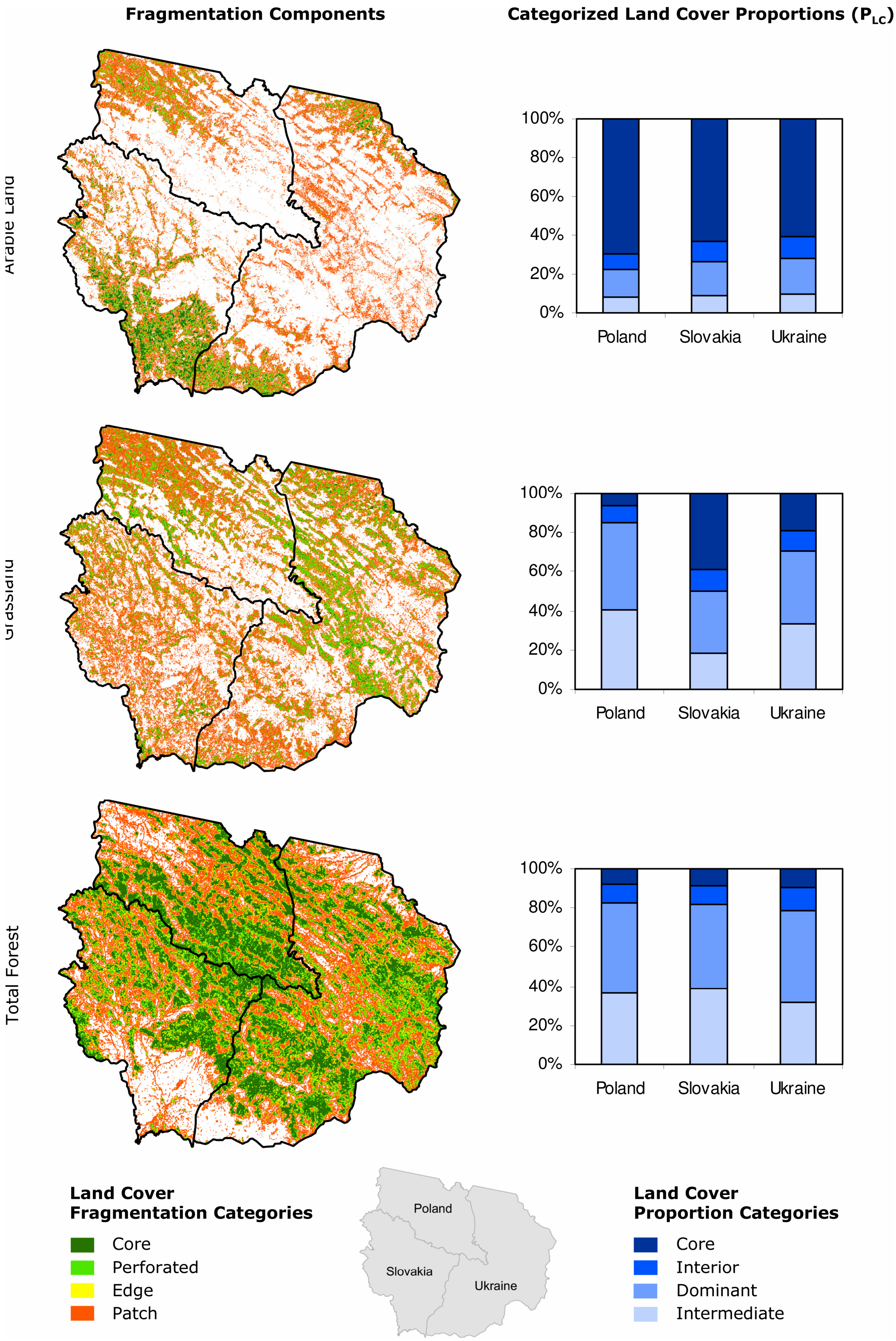


Figure II-8: Maps of fragmentation components (left) and categorized proportions of PLC with the classes core, interior, dominant, and intermediate (normalized over the sum of these components; right). Results are based in a neighborhood size of 2.25ha for arable land and grassland and on a neighborhood size of 7.29ha for the forest class.

practices are based on clear cuts. Extensive logging supported by foreign capital as well as presumably illegal forest harvesting have occurred in Ukraine in post-socialist times (Turnock 2002). Comparing valleys dissected by the Polish-Ukrainian border, we speculate that today's forest cover in Ukraine may be comparable to the extent of forest found on the Polish side before the depopulation (Figure II-5).

Table II-3: Distribution of four fragmentation components per country for the land cover types forest, arable land and grassland. Fragmentation components were calculated for three differently sized neighborhoods for the forest class (2.25ha = 5 pixels; 7.29ha = 9 pixels; 65.61ha = 27 pixels) and for two differently sized neighborhoods (2.25ha and 7.29ha) for the land cover types arable land and grassland (rows may not sum to 100% due to rounding).

		Fragmentation Component			
Land Cover Type (neighborhood size)	*Country*	*Core*	*Perforated*	*Edge*	*Patch*
Forest (2.25ha)	Poland	55.4 %	9.5 %	8.4 %	26.7 %
	Slovakia	49.9 %	11.4 %	10.3 %	28.3 %
	Ukraine	48.1 %	13.8 %	9.5 %	28.7 %
Forest (7.29ha)	Poland	37.7 %	11.6 %	14.5 %	36.2 %
	Slovakia	30.0 %	13.7 %	17.2 %	39.1 %
	Ukraine	29.1 %	15.6 %	17.4 %	37.9 %
Forest (65.61ha)	Poland	8.0 %	16.4 %	31.5 %	44.1 %
	Slovakia	3.6 %	13.3 %	31.5 %	51.7 %
	Ukraine	4.2 %	12.5 %	37.4 %	46.0 %
Arable Land (2.25ha)	Poland	2.0 %	12.9 %	6.9 %	78.2 %
	Slovakia	21.9 %	15.1 %	9.4 %	53.6 %
	Ukraine	5.1 %	9.3 %	4.5 %	81.1 %
Arable Land (7.29ha)	Poland	0.3 %	5.8 %	6.4 %	87.6 %
	Slovakia	8.9 %	11.9 %	15.5 %	63.7 %
	Ukraine	1.4 %	5.4 %	5.0 %	88.2 %
Grassland (2.25ha)	Poland	4.3 %	22.3 %	9.0 %	64.4 %
	Slovakia	3.5 %	13.5 %	6.8 %	76.2 %
	Ukraine	5.0 %	23.0 %	8.3 %	63.7 %
Grassland (7.29ha)	Poland	0.4 %	13.3 %	10.0 %	76.3 %
	Slovakia	0.3 %	6.2 %	6.8 %	86.8 %
	Ukraine	0.4 %	14.8 %	9.5 %	75.3 %

Arable land, grassland, and shrubland

The land cover map revealed considerable differences in the abundance and configuration of arable land, grassland, and shrubland between Poland, Slovakia, and Ukraine. Arable land was most dominant in Slovakia, particularly below 400m (22%) with substantial amounts between 400m and 800m (Figure II-6). Agricultural fragmentation proved to be lowest in Slovakia at all scales (e.g., core area 21.9% compared to 2% in Poland and 5% in Ukraine for the 2.25ha neighborhood) (Table II-3). The density distributions of patch size versus patch elevation (Figure II-9) revealed largest patches of arable land in Slovakia (mean patch sizes Poland 4.7ha, Slovakia 18.9ha, Ukraine 4.4ha). Poland and Ukraine had lower percentages of arable land but higher proportions of grassland (Figure II-6) and higher levels of agricultural fragmentation (Figure II-8).

Shrubland occurred almost exclusively in very small patches (Figure II-9) and highest abundances were found in Ukraine, especially above 400m (Figure II-6). The occurrence of shrubland may be interpreted as an indicator of land abandonment in all three countries, because shrubland is not expected to occur naturally below treeline apart from disturbed areas (e.g., flood plains). In total, 548km² were covered by shrubland in Ukraine compared to 140km² and 214km² in Poland and Slovakia respectively.

Differences in the abundance of arable land, grassland, and shrubland among countries are likely due to political and socioeconomic factors, especially land tenure. In Poland, the majority of non-forested land in the northern part of the study area was in private ownership throughout socialist times, but land in the south that had been depopulated after 1947 was taken by the state (Augustyn 2004). A high proportion of very small subsistence farms persisted where private ownership dominated, those areas did not change significantly during the last 60 years (Gorz and Kurek 1998; Sabates-Wheeler 2002). This is reflected in our findings through the high degree of agricultural fragmentation and a lower mean patch size of arable land (Figures 8, 9). Also, the distribution of patch sizes suggested highest levels of landscape fragmentation in Poland, where high densities of small patches of arable land and grassland co-occur.

In Poland, grassland and shrubland dominated formerly state owned land, particularly in the mountain valleys on the border with Slovakia (Figure II-5). Large areas of former state farms have been set aside or abandoned since 1990, often because they were only marginally suited for agriculture (Gorz and Kurek 1998). The Polish Forest Service claimed land that is now either reforested or undergoing secondary succession (Augustyn 2004).

In Slovakia, all land was collectivized and managed in large scale farming cooperatives (Drgona et al. 1998; Csaki et al. 2003). However, the members of the collectives continued to own their land and Slovakia restituted land to owners after 1990 (Csaki et al. 2003). Yet, our results suggested that the socialist large scale farming structure has changed little. Slovakia had larger patches (Figure II-9) and the highest share of arable land (Figure II-6) as well as significantly lower agricultural fragmentation compared to Poland and Ukraine (Figure II-8). A likely explanation is the restitution process. The vast majority of land owners left their land within the successor organizations (often co-operatives) of former collectives, for example because shares were too small to sustain economically profitable private farming. Thus, restitution in Slovakia has slowed down decollectivization and preserved Slovakia's socialist farmland patterns (Drgona et al. 1998; Mathijs and Swinnen 1998; Csaki 2000). Most shrubland in Slovakia occurred in former clear cuts, but some shrubland was also found in mountain valleys where land abandonment occurred after 1990. Many of these sites are not well suited for agriculture and were converted to arable land during the period of agricultural industrialization between 1970 and 1990 (Feranec et al. 2003).

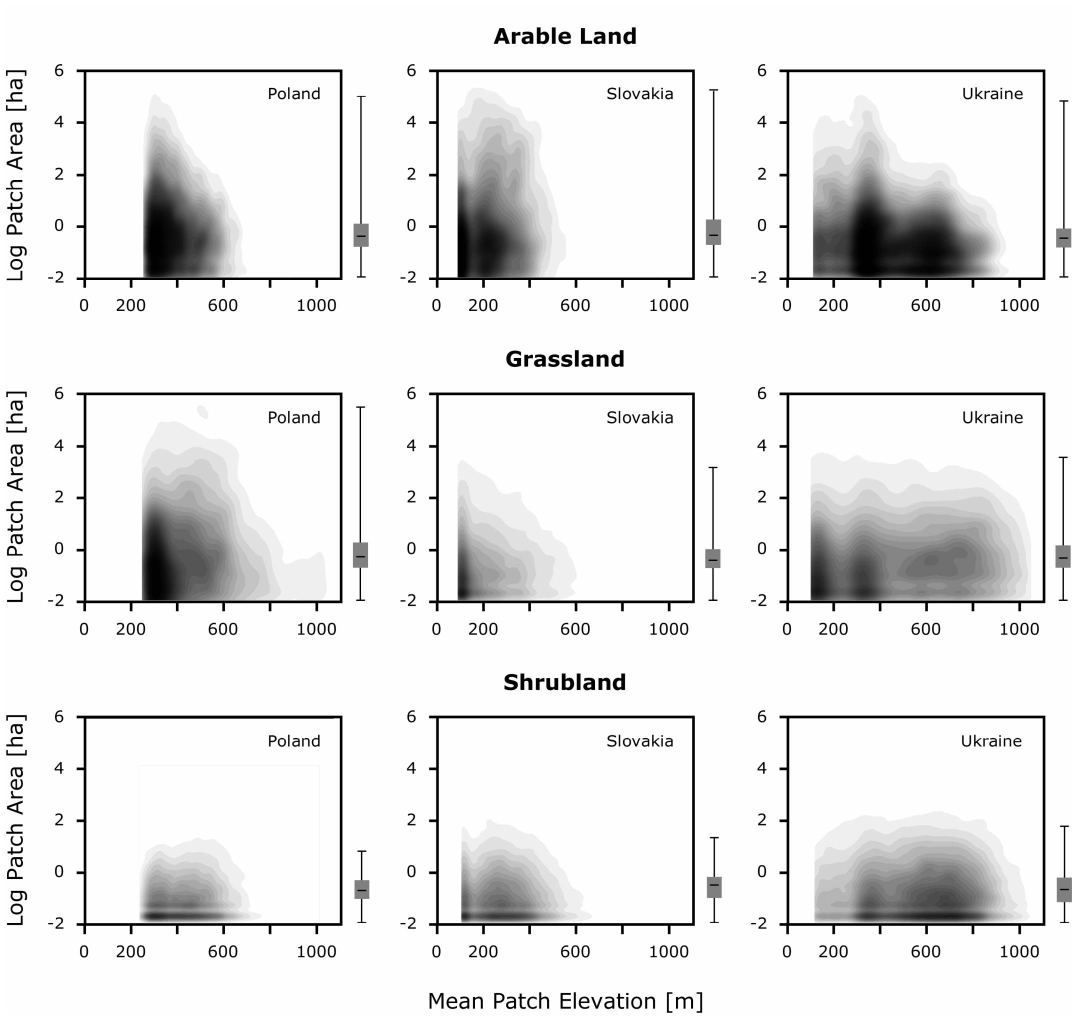


Figure II-9: Two-dimensional density distributions of logarithmized patch size [ha] and mean patch elevation [m] per country and for the land cover classes arable land, grassland and shrubland.

Landscapes in Ukraine were most strongly affected by post-socialistic changes. Arable land was completely state owned in the former Soviet Union and managed by large agricultural enterprises (Ash and Wegren 1998). Ukraine privatized land, but land reform is slow, a functioning land market is lacking, and only few private farms existed by the end of the 1990s (Ash and Wegren 1998; Lerman 1999). Some formerly state owned farms continue to operate as collectives (Ash 1998) and consequently we found many large patches of arable land, particularly at lower elevations (Figure II-9). On the other hand, much arable land was subdivided for subsistence farming, leading to a high level of agricultural fragmentation in some areas (Figure II-8). Compared to Poland or Slovakia, subsistence farming is more important in Ukraine, where settlements were found at high elevations and the mountain valleys are more populated than in the other countries. The abundances of grasslands at higher altitudes were mainly due to lower forest cover (Figure II-6), because grasslands are important as meadows for animal husbandry.

Also, arable land covered a much wider altitudinal range in Ukraine than in Poland or Slovakia (Figure II-7), and significant amounts of highly fragmented small scale agriculture existed at elevations up to 800m. It is also notable that today's agricultural fragmentation in Ukraine is comparable to Poland (Figure II-8, Table II-3), where private land ownership was common even in socialist times, although Ukraine and Slovakia had similar farming structures before 1990.

Many state owned agricultural enterprises in Ukraine went bankrupt after the system change (Ash and Wegren 1998), particularly in the Carpathians, where they often operated on marginal land (Augustyn 2004). Also, access to machinery is limited and farmers can only cultivate a small portion of the potentially available land. As a consequence, large areas have been converted to grassland or simply have been abandoned, and are undergoing secondary succession. Consequently, high abundances of grassland existed in Ukraine, especially above 400m (Figure II-6). Land abandonment is also indicated by the high amounts of shrubland in Ukraine, substantially more than in the other countries (Figure II-6), particularly at elevations above 600m where land is only marginally suited for agriculture (Figure II-9). The co-occurring patterns of three post-socialist developments in Ukraine, land abandonment, agricultural fragmentation for subsistence farming, and a preservation of parts of the large scale farming structure, are also an explanation for the high degree of landscape fragmentation for the arable land and grassland classes in Ukraine (Figure II-8).

5 Conclusions

This study compared landscapes across borders for a relatively environmentally homogeneous region in the Carpathian Mountains. To avoid potential biases arising from external factors such as study area boundaries, comparisons were based on relative proportions and land cover was stratified for elevation zones. Distinct differences in land cover and landscape pattern were found between portions of Poland, Slovakia, and Ukraine. We suggest that these differences can be attributed largely to differences in broad-scale socioeconomic and political factors.

Forest cover and composition varied considerably between the Polish, Slovak, and Ukrainian regions of the study area. For example, forest cover is higher in Poland, likely due to afforestation and natural succession following the forced depopulation in 1947. In Ukraine, Soviet forest management resulted in widespread replacement of natural forest communities with coniferous forest. Concerning agriculture, we suggest that land tenure in socialist times and the land reform chosen by the respective countries are important to explain land cover and to understand post-socialist land cover change. On formerly state owned land (virtually all land in Ukraine and some areas in Poland), land abandonment is common, often accompanied by shrub encroachment. The occurrence of shrublands is a good indicator for this process, because shrublands are not a natural vegetation formation in the area. Restitution of arable land to former owners in Slovakia led to a preservation of the large scale farming structure. However, agricultural fragmentation is highest where private land ownership was allowed in socialist times (Poland) and where state farms were dissolved and the land was made available to the people (Ukraine). For example, Ukraine showed a similar farming structure to Slovakia in socialist times, while today's agricultural fragmentation has reached a level comparable to Poland.

No study to date has conducted comparative analysis of land cover and landscape pattern between different countries in Eastern Europe. The cross-border comparison of landscapes carried out in this research may thus be an important step towards a better understanding of the consequences of the political and economic transition on land cover. For the area studied, broad-scale socioeconomic factors and policies were important to understand differences in land cover and post-socialist land change, and we suggest that they may be equally important in other areas as well.

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Chapter III:
Post-socialist forest disturbance in the Carpathian border region of Poland, Slovakia, and Ukraine

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Abstract

Forests provide important ecosystem services and protected areas around the world intend to reduce human disturbance on forests. The question is how forest cover is changing in different parts of the world, why some areas are more frequently disturbed, and if protected areas are effective in limiting anthropogenic forest disturbance. The Carpathians are Eastern Europe's largest contiguous forest ecosystem and are a hotspot of biodiversity. Eastern Europe has undergone dramatic changes in political and socio-economic structures since 1990, when socialistic state-economies transitioned towards market economies. However, the effects of the political and economic transition on Carpathian forests remain largely unknown. Our goals were to compare post-socialist forest disturbance, and to assess the effectiveness of protected areas in the border triangle of Poland, Slovakia, and Ukraine, to better understand the role of broad-scale political and socio-economic factors. Forest disturbances were assessed using the forest disturbance index derived from Landsat MSS/TM/ETM+ images from 1978–2000. Our results showed increased harvesting in all three countries (up to 1.8 times) in 1988-1994, right after the system change. Forest disturbance rates differed markedly among countries (disturbance rates in Poland were 4.5 times lower than in Ukraine, and 4.3 times lower than in Slovakia), and in Ukraine, harvests tended to occur at higher elevations. Forest fragmentation increased in all three countries, but experienced a stronger increase in Slovakia and Ukraine (~ 5% decrease in core forest) than in Poland. Protected areas were most effective in Poland and in Slovakia, where harvesting rates dropped markedly (up to 9 times in Slovakia) after protected areas were designated. In Ukraine, harvesting rates inside and outside protected areas did not differ appreciably, and harvests were widespread immediately before the designation of protected areas. In summary, the socioeconomic changes in Eastern Europe that occurred since 1990 had strong affects on forest disturbance. Differences in disturbance rates among countries appear to be most closely related to broad-scale socio-economic conditions, forest management practices, forest policies, and the strength of institutions. We suggest that such factors may be equally important in other regions of the world.

1 Introduction

Anthropogenic land use is a major driver of change in terrestrial ecosystems and has modified more than half of the Earth's land surface (Vitousek et al. 1997; Foley et al. 2005). Forest ecosystems provide many structures and services that are essential for humanity, including the protection of biodiversity and carbon sequestration (Goodale et al. 2002; Randolph et al. 2005). Assessing changes in forest ecosystems and understanding their underlying causes is therefore of great concern. Global forest cover has been greatly reduced in the last centuries (Goldewijk 2001), and continues to diminish, particularly in the tropics (Lepers et al. 2005). The extent (Skole and Tucker 1993; Achard et al. 2002) and underlying causes (Pfaff 1999; Geist and Lambin 2002) of tropical deforestation have received much attention. However, in other regions forests are increasing (Rudel et al. 2005), or forest cover trends are unknown, and a better understanding of forest cover change across the globe is needed.

Central and Eastern Europe still have large and relatively wild forests (Mikusinski and Angelstam 1998; Oszlanyi et al. 2004; Wesolowski 2005). The Carpathian mountain range presents Europe's largest continuous mountain forest ecosystem and is an important carbon pool, due to the high proportions of stands in higher age classes and the high productivity of Carpathian forests (Nijnik and Van Kooten 2006). Being a bridge between Europe's south-western and south-eastern forests, the Carpathians also serve as an important refuge and corridor for plants and animals (Perzanowski and Szwagrzyk 2001; Webster et al. 2001). The Carpathians harbor high levels of biodiversity with a large number of endemic species; over one third of all European plant species (Perzanowski and Szwagrzyk 2001); and habitat for Europe's largest populations of brown bear (*Ursus arctos*), wolf (*Canis lupus*), lynx (*Lynx lynx*), wildcat (*Felis sylvestris*), and European bison (*Bison bonasus*) (Webster et al. 2001; Oszlanyi et al. 2004). Yet, relatively little is known about recent landscape changes in the Carpathians and spatially explicit information on changes in habitat conditions is scarce.

Eastern Europe has experienced drastic changes in political, societal, and economic structures following the fall of the Iron Curtain in 1990. The transition from command economies to market-oriented economies had powerful impacts on land management and land use (GLP 2005), and resulted in forest cover change in many areas across Eastern Europe, for example in the Czech Republic (Bicik et al. 2001) or in Poland (Augustyn

2004). In areas where socialist forest management overexploited forests (Turnock 2002), forest cover has partially increased since 1990 (Peterson and Aunap 1998; Bicik et al. 2001). Conversely, privatization of forests may have increased harvesting rates (Eronen 1996; Turnock 2002) and illegal clear cutting has occurred in some areas (Nijnik and Van Kooten 2000). We were particularly interested in assessing forest disturbance, which is the removal of forest cover by way of natural events (e.g., insect outbreaks, windfall), or anthropogenic activities (e.g., logging, infrastructure development). Little quantitative information on the rate and spatial pattern of disturbances in Eastern Europe's forest ecosystems is available for the post-socialist period. The question of how the political and economic transition affected forests, remains, especially in the Carpathian Mountains, where biodiversity is potentially threatened due to logging activities, which may lead to the fragmentation and degradation of forests.

Beyond the urgent need to assess forest disturbances in Eastern Europe, the region offers unique opportunities to better understand the role of socio-economics for land dynamics (GLP 2005; Kuemmerle et al. 2006). Laws, policies and institutions exert strong influence on land users and land management (Lambin et al. 2001; Dietz et al. 2003), and changes in broad-scale socio-economic and political determinants can trigger land change. However, the relative importance of broad-scale factors on land cover dynamics is not well understood (GLP 2005). Land management policies and institutions in Eastern Europe changed dramatically after 1990. Assessing post-socialist land changes may thus reveal important insight into the effects of changing institutions on land cover (GLP 2005).

Cross-national studies in environmentally homogeneous regions are particularly interesting, because they allow relating differences in land dynamics to differences in socio-economics and policies (Kuemmerle et al. 2006). The Carpathian Mountains are well suited for trans-border comparisons, because the region is environmentally relatively homogeneous (UNESCO 2003), yet heavily dissected by country borders. The region was part of the Austro-Hungarian Empire for a period of about 150 years prior to 1918 (Turnock 2002), during which land management policies and land use were fairly homogeneous. However, in post world war II socialist times, the Soviet Union and other Eastern European countries were distinctly different in politics and socio-economics (Lerman 2001). After 1990, countries chose different approaches and rates in their transition to market-oriented economies (Lerman 2001). Comparison of post-socialist change in forest ecosystems (e.g., measured through disturbance rates) for border regions in the Carpathians thus offers unique opportunities to relate socioeconomic and political differences among countries to differences in land cover change.

Protected areas are important for conserving biodiversity (Myers et al. 2000), and several protected areas were established in the Carpathians to protect the region's unique forest ecosystems (e.g., UNESCO 2003). Protected areas face threats from human activities both within their boundaries, and in their surrounding areas (Chape et al. 2005). Although protected areas stop habitat loss in most cases (Bruner et al. 2001; Stoyko 2004), land-use and land-cover change in their neighborhood often reduces adjacent habitat (DeFries et al. 2005; Naughton-Treves et al. 2005), which is problematic for area sensitive species (Woodroffe and Ginsberg 1998). It is therefore crucial to quantify the effectiveness of protected areas and their management (Chape et al. 2005). This is commonly measured by comparing forest disturbance rates within protected areas and their neighborhoods (Bruner et al. 2001; Naughton-Treves et al. 2005). Transboundary protected areas are particularly interesting, because forest disturbance rates inside and outside protected areas can be compared among countries. Differences between neighboring countries are likely due to differences in protected area management, institutions, and socio-economic factors such as population density, rural income, or attitude towards protected areas. Cross-border comparison thus allows for a better understanding of the relative importance of broad-scale determinants for the effectiveness of protected areas.

Comparing rates and spatial pattern of forest disturbances among countries in the Carpathians is not an easy task, because conventional datasets such as forest inventory maps and statistical data are either missing or differ in scale and accuracy (Nijnik and Van Kooten 2000; Filer and Hanousek 2002). Moreover, illegal forest harvesting may be common (Nijnik and Van Kooten 2000), but is not included in official forestry statistics, thus limiting the use of such statistics. An alternative is to map forest disturbances using satellite images (Coppin and Bauer 1996; Radeloff et al. 2000; Broadbent et al. 2006), because it provides current and retrospective land cover information, independent from country borders and in an efficient manner for large areas. The forest disturbance index (Healey et al. 2005) has recently been developed, but was so far only tested in the northwestern United States and in northern Russia. Landsat satellite data is particularly well suited for forest disturbance detection because of its relatively high resolution (80m for Landsat Multispectral Scanner (MSS), and 30m for Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+)), and continuous data record since 1972, making it the most important data source for land cover change analyses (Cohen and Goward 2004).

Our study area was the border triangle of Poland, Slovakia, and Ukraine (Figure III-1). These three countries exhibited strong differences in socio-economic and political determinants both before and after 1990, and this has affected forest ecosystems in our study area and resulted in differences in forest cover and forest composition among the countries. For example, the Ukrainian region of the study area has abundant coniferous forest whereas mixed and broad-leaved forests dominate in the Polish and Slovak region of the study area (Kuemmerle et al. 2006). The question remains however, how much of such differences are due to recent changes in the post-socialist period versus pre-1990 socialist forest management. In other words, have the three countries converged since 1990 in terms of their forest cover and patterns due to the fundamental shift from a planning economy to a market-oriented system, or have they diverged?

The overarching goal of our study was to monitor post-socialist forest disturbance for the border triangle of Poland, Slovakia, and Ukraine in the Carpathians, because of the region's value for nature conservation and its high biodiversity, and because cross-border comparison of forest disturbance may also provide unique insights about the role of broad-scale socioeconomic factors, policies, and institutions on land change.

Our specific objectives were thus to:

(1) quantify post-socialist forest disturbance and make a cross-border comparison for parts of the countries Poland, Slovakia, and Ukraine in the Carpathians

(2) assess the effectiveness of protected areas in each country by comparing forest disturbance inside and outside protected areas

(3) test the newly developed forest disturbance index in temperate mixed forests in order to measure forest disturbance between 1988 and 2000

2 Study area

The study area covers 17,700km^2. Study area boundaries were based on administrative borders, the extent of one Landsat TM scene, and landscape features such as rivers. Altitudes vary from 100 to over 1,300m above sea level. The bedrock is largely dominated by sandstone and shale (Denisiuk and Stoyko 2000; Augustyn 2004), but some andesite-basalts occur in the southwest of the study area (Herenchuk 1968). With average annual precipitation of about 1,200mm and an annual mean temperature of 5.9°C (at 300m), the climate is moderately cool and humid with marked continental influence (Augustyn 2004).

Our study area represents one ecoregion, but contains three altitudinal zones of potential natural vegetation (Perzanowski and Szwagrzyk 2001). The foothills (< 600m) are mostly covered by broad-leaved forests, consisting of European beech (*Fagus sylvatica*), pedunculate oak (*Quercus robur*), sessile oak (*Quercus petraea*), lime (*Tilia cordata*), and hornbeam (*Carpinus betulus*). The montane zone (600-1,100m) is dominated by European beech (*Fagus sylvatica*), mixed with silver fir (*Abies alba*), Norway spruce (*Picea abies*), sycamore (*Acer pseudoplatanus*), and white alder (*Alnus incana*) (Novotny and Fillo 1994; Grodzinska and Szarek-Lukaszewska 1997; Perzanowski and Szwagrzyk 2001). The timberline of dwarfed beech (1,100-1,200m) directly borders alpine meadows on hilltops (Denisiuk and Stoyko 2000). The study area is environmentally relatively homogeneous (UNESCO 2003), however, local climate variations and topography result in a natural variability of forest types and forest composition (Denisiuk and Stoyko 2000). For instance mixed beech/fir forests are the natural vegetation on north-facing slopes, whereas pure beech forests would dominate south-facing slopes without anthropogenic influence. Forests in the study area are characterized by their high productivity, with annual increments in standing volume reaching up to 6m³ per hectare (Nijnik and Van Kooten 2000; MASR 2003).

The study area harbors several protected areas (Figure III-1). The 29,000ha Bieszczady National Park in Poland was founded in 1973 and enlarged several times until 1999. In 1992, the Polish-Slovak biosphere reserve was designated consisting of Bieszczady National Park two newly founded Polish landscape parks (San Valley and Cisniansko-Wetlinski), and the 46,000ha Poloniny National Park in Slovakia. The biosphere reserve was transformed into the trilateral East Carpathians Biosphere Reserve, when the Ukrainian Nadsanski Landscape Park (founded in 1997) and the Uzhanski National Park were joined in 1999 (Denisiuk and Stoyko 2000). The 39,000ha Uzhankski National Park was also designated in 1999. Altogether, the East Carpathian Biosphere Reserve covers an area of about 213,000ha (53% in Poland, 19% in Slovakia, and 28% in Ukraine). The biosphere reserve (Figure III-1) consists of a strictly protected core zone, a buffer zone, where conservation is emphasized, but sustainable land use and tourism are allowed, and a transition zone, where sustainable land use and development is promoted (Denisiuk and Stoyko 2000; UNESCO 2003). Another protected area, the 40,000ha Skole Beskydy National Park, was established in 1999 in the Ukrainian region of the study area.

Although some of Europe's last remaining primeval forests are found in the study area, forest management has a long tradition in the region (Novotny and Fillo 1994; Augustyn 2004), and intensive land use has substantially affected most forests, creating a complex pattern of forests, arable land, and pastures (Grodzinska and Szarek-Lukaszewska 1997; Denisiuk and Stoyko 2000; Kuemmerle et al. 2006). Forest cover decreased markedly in the 18th and the first half of the 19th century due to population growth and land use intensification (Augustyn 2004). Since the 19th century, forest cover has generally increased (Kozak 2003). However, after World War II socialist forest management overexploited forest resources and logging rates again became unsustainably high in many areas (Turnock 2002). Some areas in the Polish region of the study area were depopulated after 1947 following border changes between the Soviet Union and Poland (Turnock 2002) and large areas were converted to forests (Augustyn 2004).

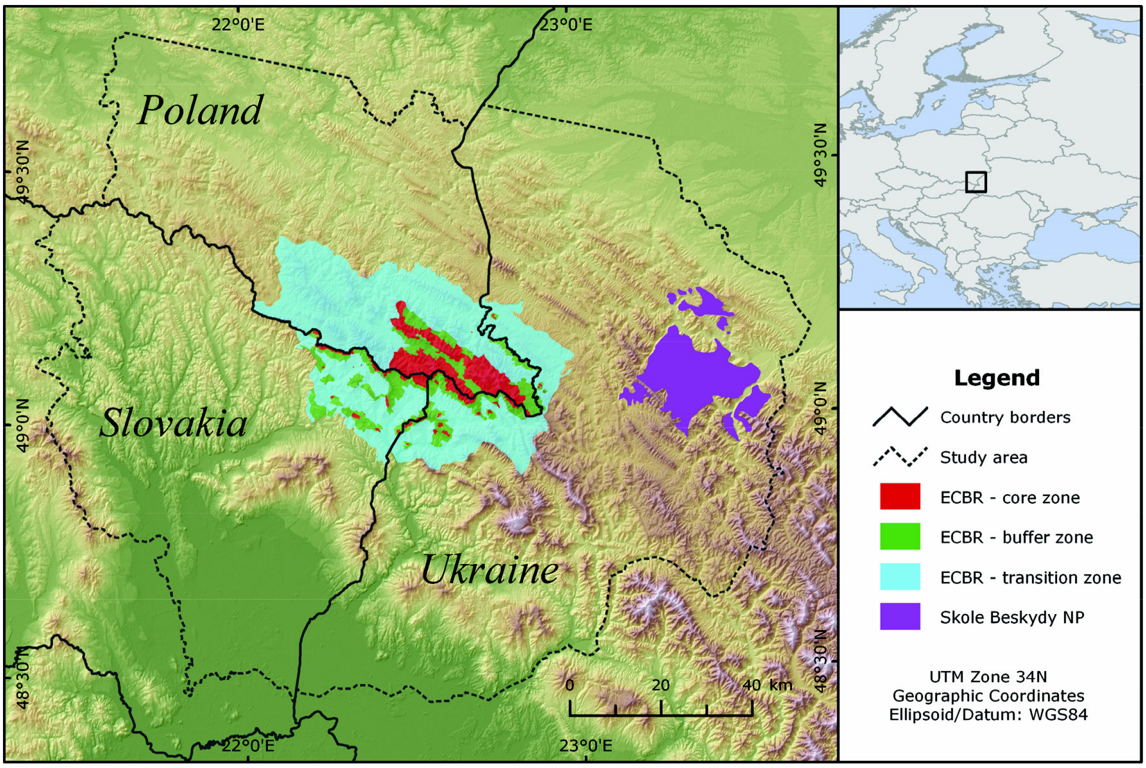

Figure III-1: Location of the study area in the Carpathian Mountain range. The study area harbors two protected areas, the trilateral East Carpathians Biosphere Reserve (ECBR) and the Skole Beskydy National Park (NP) in Ukraine (elevations range from about 100-1,700m; data sources: SRTM digital elevation model, ESRI Data and Maps Kit).

Forestry is an important factor for the local economy of the area (Antoni et al. 2000; Turnock 2002), and the majority of the forests in all three countries are used commercially. Most of the harvested timber is used to meet the demand of wood products in the respective countries and is not exported (Eronen 1996; MASR 2003). In Poland and

Ukraine, harvested timber is mainly processed to sawnwood, particle board, used for paper and cardboard production, and to manufacture furniture (Andousypine 1994; Buksha et al. 2003; FAO 2005). In Slovakia, most timber is used for producing pulp for the paper and cardboard industry, and for sawnwood (MASR 2003). Forest management has changed the forest composition in many areas and led to widespread replacement of natural forest ecosystems with Norway spruce and Scots pine monocultures (*Pinus sylvestris*) (Perzanowski and Szwagrzyk 2001; Augustyn 2004; Kruhlov 2005). The age compositions of forests in Poland and Slovakia are relatively close to an even distribution and most trees are found in mature age classes (Röhring 1999; MASR 2003). However, in Ukraine the age distribution is severely skewed towards young age classes, and less than 30% of all forests are mature (Strochinskii et al. 2001). The rotation age in commercially used forests varies depending on the species composition, but is on average around 80-120 years in Ukraine, and 100-120 years in Poland and Slovakia (MASR 2003). Forest disturbance in the study area is largely anthropogenic, consisting mainly of logging and infrastructure development (Schelhaas et al. 2003). Natural disturbance events (e.g., insect defoliation, avalanches, and windthrow) are largely confined to plantations (Nilsson and Shvidenko 1999).

The transition from command to market oriented economies has affected the forestry sector and led to changes in forest ownership, management policies, and institutions. In socialist times, nearly all forests in the study area were state owned (Turnock 2002), but forest management differed among countries. For example, clear cuts were common in Ukraine and Slovakia, whereas selective logging dominated in the Polish region of the study area. After 1990, each country adopted a different transition strategy (Kissling-Naf and Bisang 2001), changing forest management and ownership patterns. Forests remained largely state owned in Ukraine and Poland, whereas Slovakia restituted forest to former owners (MASR 2003; FAO 2005). New forest management policies committed to multifunctional forestry were adopted in many Eastern European countries to comply with international agreements such as the Rio Protocol and the Helsinki Initiative (Kissling-Naf and Bisang 2001). In addition, Poland and Slovakia strived to meet European Union (EU) environmental standards in preparation of their accession to the EU (Eronen 1996). The demand for forestry products increased in Poland after 1992 and remained relatively stable in Slovakia, but has decreased considerably in Ukraine throughout the 1990s (Eronen 1996; MASR 2003).

Little quantitative information is available on how changes in forest ownership and forest legislation affected forest cover in the Carpathians. Official statistics are spatially coarse and overlook illegal forest activities. Remote sensing is the most feasible way to derive spatially explicit change information for large areas and across country borders. A few studies used remote sensing images to assess forest cover change in the Carpathians, but they were either restricted to small areas or rely on coarse resolution data (Kozak et al. 1999; Otahel and Feranec 2001; Kruhlov 2005). Coordination of Information on the Environment of the European Union (CORINE) 1:100,000 land cover data and Landsat MSS images showed an intensification of agriculture in Slovak mountain valleys and a 9% loss in forest cover for the period 1976 to 1990 (Feranec et al. 2003). Historic maps and contemporary satellite images show increasing forest cover during the 20th century for several areas in the Carpathians (Angelstam et al. 2003; Kozak 2003; Augustyn 2004). Comparison of global land cover maps (at 1km spatial resolution) for sub-catchments of the Tisza River in Ukraine showed a mean forest loss of 5% from 1992 to 2001 (Dezso et al. 2005). To our knowledge, no study has quantified Carpathian forest cover change for the post-socialist period at sufficient spatial detail and across borders.

3 Data and methods

3.1 Datasets used

We acquired 5 Landsat TM and ETM+ images (path/row 186/26: 10th June 2000, 4th July 1994, 2nd June1994, 27th July 1988, and 2nd October 1986), and 4 Landsat MSS images (path/row 200/26: 30th July 1977; 200/25: 16th May 1979; 201/25: 2nd September1979; and 201/25: 2nd July 1979). Thermal bands were not retained. The Space Shuttle Radar Topography Mission (SRTM, Slater et al. 2006) digital elevation model (DEM) was resampled to 30m using bilinear interpolation to match the Landsat TM data. The borders of the protected areas were provided by the Geography Department of the Ivan-Franko University (Lviv, Ukraine).

To validate the accuracy of our forest disturbance map, ground truth points were gathered in the field, from ancillary datasets, and from the Landsat images. Field work was carried out in summer of 2004, spring of 2005, and spring of 2006, using non-differential Global Positioning System (GPS) receivers. To cover broad areas, and to avoid deterioration of the GPS signal under closed canopies, some areas were photo-documented from view points (e.g., mountain ridges). The view points were georeferenced using GPS receivers, and the view angle and distance of the area depicted in the photo were noted. This allowed digitizing ground truth points on screen using the Landsat images and topographic maps as geometric references (Kuemmerle et al. 2006). Sixteen Quickbird and three IKONOS images (acquired between 2002 and 2005), and forest inventory maps and stand statistics from 1995 – 1999 for parts of Poland (obtained from the Polish Forest Administration), were used to collect additional ground truth points. Clear cuts frequently occurred in remote areas, for example away from roads or at higher altitudes, where mapping in the field was not feasible. To include these areas in our accuracy assessment, we digitized ground truth points for bigger clear cuts directly on the Landsat images. We included ground truth points only where land cover was locally homogenous (i.e., 3x3 Landsat TM pixels) to minimize positional uncertainty and collected about 450 ground truth points each in three categories: unchanged forest, non-forested, and forest disturbances. In total, 1,347 control points were gathered (587 based on ground visits, 430 from ancillary datasets, and 330 from the Landsat data).

3.2 Preprocessing of Landsat TM and ETM+ data

Change detection requires precise geometric correction of images, because misregistration and relief displacement decrease change detection accuracy (Coppin et al. 2004). We first referenced the June 2000 Landsat image to the Universal Transverse Mercator (UTM) coordinate system (World Geodetic System 1984 datum and ellipsoid), using the SRTM digital elevation model as a base map. To better match the June 2000 Landsat image, the SRTM DEM was shaded using sun azimuth and elevation from the Landsat acquisition date and time. Ground control points were collected semi-automatically using correlation windows (Itten and Meyer 1993; Kuemmerle et al. 2006). Once the June 2000 image was georeferenced, we co-registered all other satellite images to that image. Remaining positional errors were low (root mean square errors 0.16 to 0.26 pixels).

Removing atmospheric influence and differences in illumination due to topography can improve change detection accuracy (Song et al. 2001). We applied calibration coefficients to estimate at-satellite radiance (Chander et al. 2004) and a modified 5S radiative transfer model that incorporates a terrain dependent illumination correction (Radeloff et al. 1997) to calculate surface reflectance. To prevent overcorrection in areas of low illumination, the Minnaert constant (Itten and Meyer 1993) was set to 0.75 for the October image. Comparison of neighboring spectra from shaded and unshaded hillsides and visual assessments confirmed successful atmospheric and topographic correction

3.3 Forest disturbance detection

Mapping forest disturbance digitally provides quantitative change information and is more repeatable than visual image interpretation (Coppin and Bauer 1996; Coppin et al. 2004). Tasseled Cap indices (Crist and Cicone 1984) are commonly used for change analysis (Collins and Woodcock 1996; Franklin et al. 2001; Wulder et al. 2006). This transformation reduces the data dimension while emphasizing forest related features (Dymond et al. 2002; Healey et al. 2005) and leads to higher change detection accuracies (Collins and Woodcock 1996; Healey et al. 2005). Based on tasseled cap transformation, the disturbance index (Healey et al. 2005) provides a single index identifying areas where forest cover declined. The index assumes that forests are characterized by high greeness and wetness components, whereas disturbances will display low greeness and wetness, but high brightness. The index requires masking out all non-forest areas. After normalizing the individual Tasseled Cap components to a mean of zero and a standard deviation of one, the disturbance index is calculated as Brightness minus the sum of greeness and wetness. Categorical change maps result from multitemporal classifications of the disturbance index images (Healey et al. 2005).

We applied the forest disturbance index in our study area. The 1986-88 imagery was used to separate forest from non-forest. The MSS data from 1977-79 were only used to determine if forest openings in the 1986-88 imagery were clear-cuts (and forested in 1977-79) or permanent openings. Post-socialist forest disturbances were assessed by calculating disturbance index images for 1988, 1994, and 2000, and conducting a maximum likelihood classification for the combined data (Figure III-2). Our satellite analysis can not distinguish between anthropogenic and natural disturbance, and we thus labeled all changed areas generically as disturbance, but it is important to note that the vast majority of these disturbances are due to forest harvesting, because large-scale natural disturbances are rare (Schelhaas et al. 2003).

Separating forested and non-forested areas for 1988

Separation of forest and non-forest can be challenging for some forest classes when using single-date imagery. For instance, young broad-leaved forests and meadows can be spectrally similar in summer images. Phenology information inherent in multitemporal imagery allows to distinguish such classes (Dymond et al. 2002; Zhang et al. 2003). We used unsupervised Iterative Self-Organizing Data Analysis (ISODATA) to cluster the autumn image (2nd October 1986) into 40 classes (Figure III-2). Clusters were labeled as forest, non-forest, or temporarily assigned to a mixed class if they were ambiguous. Mixed classes were further subdivided with ISODATA (using 10-20 classes) based on the summer image (27th July 1988), to assign all sub-clusters to the classes forest or non-forest. Water pixels were masked out using thresholds for the near and mid-infrared bands of the 1988 image. To exclude small areas that are functionally not forest (e.g., hedges, gardens, riparian buffers), we labeled all patches below a threshold of 30 pixels as non-forest. This threshold was derived based on high-resolution images and field visits.

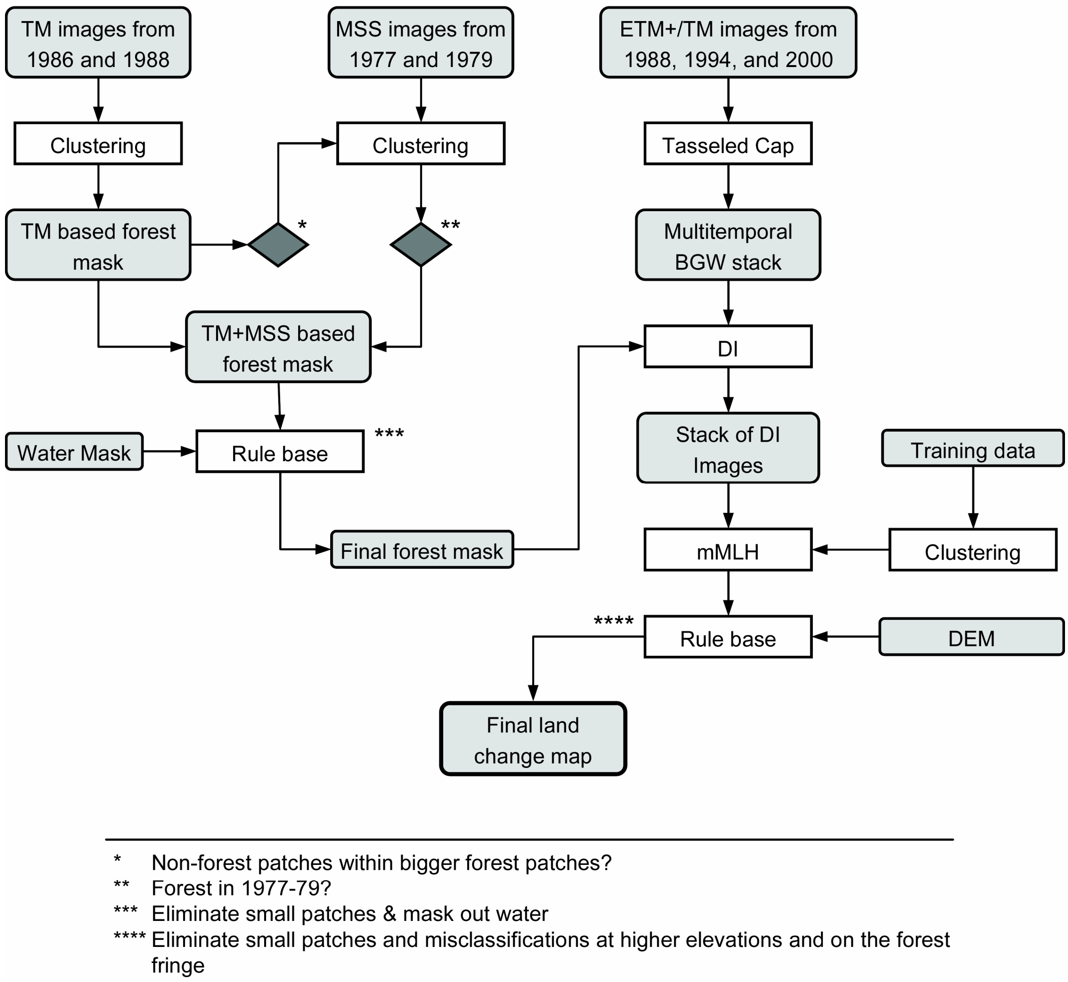

Figure III-2: Processing scheme for detecting forest disturbance in the study area (for details compare to section 3.2; BGW = Tasseled Cap brightness, greenness, and wetness; DI = disturbance index; mMLH = multitemporal maximum likelihood; DEM = digital elevation model).

Four Landsat MSS images from 1977 and 1979 together covered the entire study area and were used to check whether openings in 1988 represented forest disturbances or permanent clearings (Figure III-2). First, we identified all non-forest patches that were within larger forest patches in the TM-based forest/non-forest map as potentially disturbed areas. Ground truth and visual assessment showed that all potential disturbances smaller than 21 TM-pixels were indeed disturbed areas, and no disturbances exceeded 1,000 TM-pixels

(90ha). The remaining patches (> 21 pixels and < 1,000 pixels) were subset from the MSS imagery while retaining the spatial resolution of the TM images. Second, this subset was subdivided into forest and non-forest pixels using ISODATA clustering for each MSS image. Because the overall number of pixels in each subset was low (between 0.03 and 0.71% of the study area), 10-20 classes were sufficient to accurately identify disturbed areas in 1988 and these disturbances were included in the forest class.

Detecting forest disturbances for the period 1988-2000

The disturbance index (Healey et al. 2005) was calculated for each year (Figure III-2). Individual bands were stacked into a composite image and a combination of unsupervised and supervised classifications was used to identify “unchanged forest”, “disturbance 2000-1995”, “disturbance 1994-1989”, and “disturbance before 1988”. We digitized 60 circular training areas (7ha each) for unchanged forest based on the Landsat images, forest inventory maps, and expert knowledge. For each of the disturbance classes, between 22 and 27 of the larger disturbances were digitized on screen. All training data were independent from accuracy assessment data. Training polygons were clustered using ISODATA, and unambiguous clusters were used as training signatures for a maximum likelihood classification (guided clustering, Bauer et al. 1994) Additional training signatures were gathered interactively for areas where misclassifications occurred.

The TM images from 1994 and 1988 contained a few clouds (0.9 % and 2.2% of the study area respectively). For those areas, disturbance index images were calculated from additional images. The 1988 image was substituted with an image from 1986, whereas for 1994 two images were available. Because the area affected by clouds was very small for 1994 and 1988, thresholds proved to be sufficient to separate changed from unchanged areas. Some errors of commissions of disturbances occurred at elevation higher than 1050m, due to phenological differences between the images, and these areas were labeled as unchanged. To remove noise due to misclassifications, patches smaller than 7 pixels were eliminated (treating all forest disturbances as a single class to retain heterogeneity among disturbance classes) and assigned to the dominant surrounding land cover of either non-forest or unchanged forest. The threshold was determined based on visual assessment of very-high resolution images and ground truth. Some misclassifications occurred at the forest fringe (typically 1-2 pixels wide). Such patches were selected based on their geometry and neighborhood characteristics and assigned to either forest or non-forest based on the disturbance image of 2000.

Disturbance data was summarized for the three periods covered by the Landsat TM/ETM+ data (before 1988, 1988-1994, and 1994-2000). We calculated annual disturbance rates by dividing the disturbed area for a given time period by six, thereby assuming disturbances detected in 1988 also had occurred in a six year period. To compare forest disturbances inside and outside protected areas, disturbance rates were calculated separately for each of the protected areas and outside protected areas for each country.

Forest type stratification for changed areas

To assess the type of forest affected by disturbances, we stratified 1994 and 2000 disturbed areas into broad-leaved forest, mixed forest, and coniferous forest based on the Tasseled Cap transformed 1988 Landsat image. To evaluate the accuracy of the forest type classification, we also included some areas of unchanged, mature forest where ground truth had been mapped (Kuemmerle et al. 2006), and we used a stratified random sample of 250 such plots. We clustered the combined dataset using ISODATA into 30 classes which were labeled using expert knowledge and independent field data. Clouded areas in the 1988 image were classified using the same approach, but based on the October 2nd 1986 image. Statistics were calculated based on the disturbed areas only. Disturbances in 1988 were not stratified into forest types due to the lack of ground truth data for the MSS images.

3.4 Forest fragmentation

Forest fragmentation may introduce edge effects, lead to habitat loss, and result in a loss of forest biodiversity (Gascon and Lovejoy 1998; Debinski and Holt 2000; Riitters et al. 2002). Traditional landscape indices (O'Neill et al. 1988a) and spatially explicit fragmentation measures (Riitters et al. 2002) can quantify forest fragmentation. We calculated the mean patch size and the area-weighted mean patch size of all disturbance patches for the three countries to examine forest disturbance sizes. The area-weighted mean patch size equals patch area (m^2) divided by the sum of patch areas (McGarigal 1994). To exclude micro-patches from the analysis, the forest disturbance map was majority filtered using a kernel size of 3x3. To quantify changes in forest fragmentation, we used Riitters et al. (2002) indices. Riitters indices compare the proportion of forest (Pf) and forest connectivity (Pff) in a window around each pixel. Pff is an approximation of the probability that a forest pixel is located next to another forest pixel (Riitters et al. 2002). Each pixel was categorized as either “core” (Pf = 1), “perforated” (1 > Pf ≥ 0.6 and Pf >

Pff), "edge" (1 > Pf ≥ 0.6 and Pf ≤ Pff), or "patch" (Pf < 0.6). We chose a neighborhood size of 9x9 pixels based on prior research (Kuemmerle et al. 2006).

4 Results

The forest disturbance analysis revealed major changes in post-socialist times in all three countries (Figure III-3), but the nature and extent of changes differed markedly among countries and time periods. In Poland, disturbances were overall rare. Slovakia showed a heterogeneous pattern of disturbances stemming from both socialist times and the post-1990 transition period, particularly along the border to Poland. In Ukraine, disturbances were frequent and mainly clustered in the center and the northern slope of the Carpathians (Figure III-3).

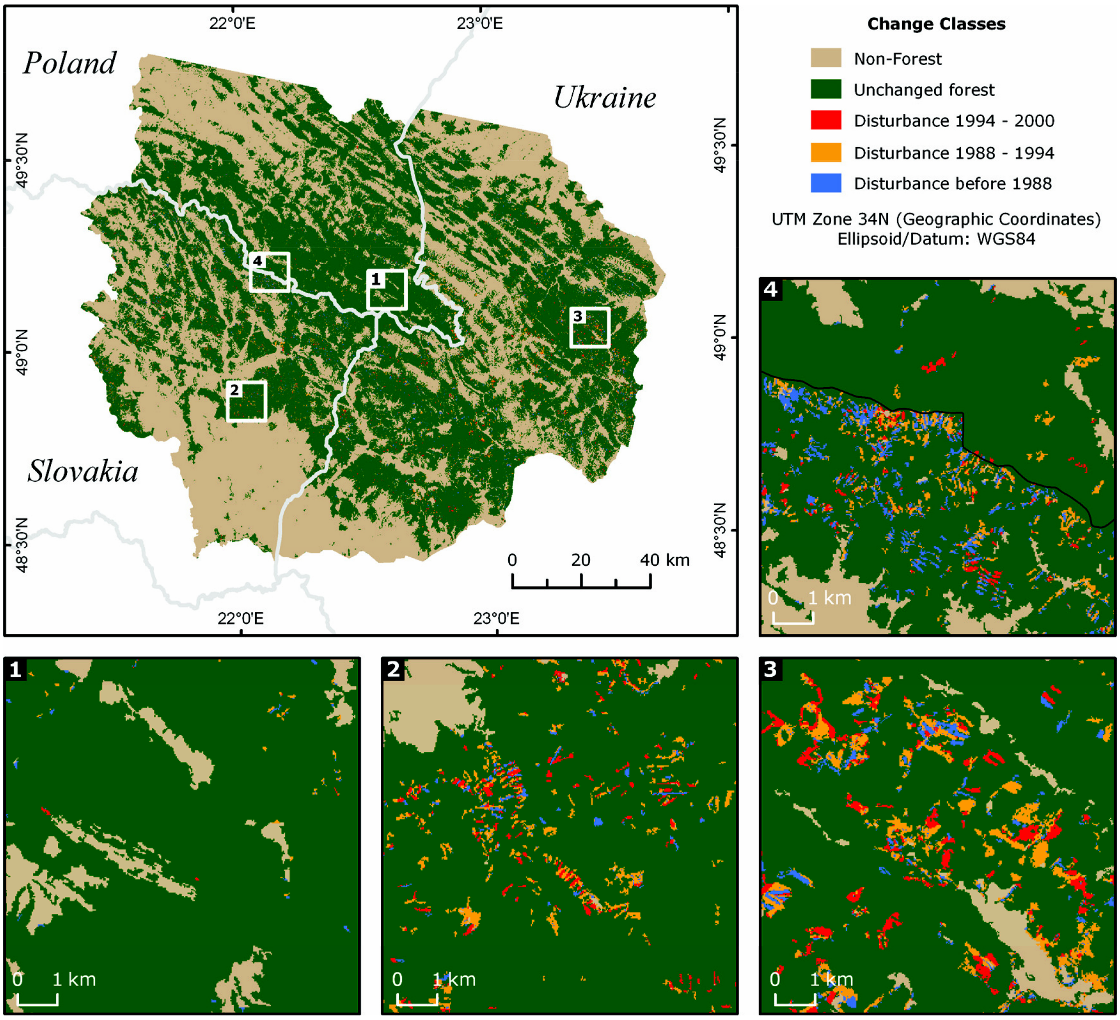

Figure III-3: Forest disturbance map of the study area. The insets provide examples of disturbance patterns of the countries Poland (inset 1), Slovakia (2), Ukraine (3) and the Polish-Slovak border region (4).

Our classification of the forest disturbance index resulted in a precise forest disturbance map with an overall accuracy of 94.8% and an overall kappa (Foody 2002) of 0.93, and conditional kappa values above 0.95 for all three periods. Producer's accuracy was equally high, with the exception of 1988 where accuracy was 81%, mainly due to confusion with unchanged forest (Table III-1). Forest was the dominating land cover type in the region covering 51% in 1988. At higher altitudes, forest cover was much higher, increasing to almost 100% cover above 800m. Below 800m, forest cover was much lower in Ukraine compared to Poland and Slovakia, particularly at altitudes between 400m and 800m.

Table III-1: Error matrix for the forest disturbance detection (Values represent absolute numbers of ground truth plots; UAC = user's accuracy [%]; PAC = producer's accuracy [%]).

		Reference Data						
		NF	F	D2000	D1994	D1988	∑	UAC
Classified Data	Non-Forest (NF)	**440**	10	5	3	7	465	94.6
	Unchanged Forest (F)	7	**431**	12	2	13	465	92.7
	Disturbances in 1994-2000 (D2000)	0	1	**194**	3	0	198	98.0
	Disturbances in 1988-1994 (D1994)	0	1	2	**120**	1	124	96.8
	Disturbances before 1988 (D1988)	0	1	0	2	**92**	95	96.8
	∑	447	444	213	130	113	1347	
	Producers Accuracy (PAC)	98.4	97.1	91.1	92.3	81.4		
	Conditional Kappa	0.92	0.89	0.98	0.96	0.97		

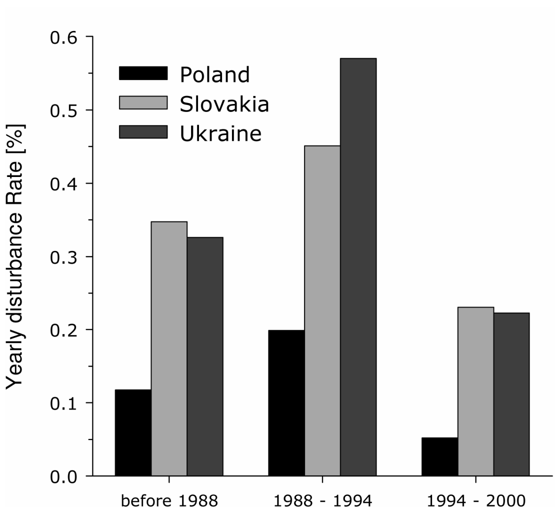

Figure III-4: Yearly disturbance rates for the Polish, Slovakian, and Ukrainian region of the study area (Note: Disturbance rates before 1988 were referenced to a six year interval).

In total, 510km² of forest were disturbed (5.38% of the total forest area), and 353km² (3.72% of the total forest area) of the disturbances occurred after 1988. Disturbance rates were generally moderate and similar trends occurred in all three countries. Disturbance rates increased in 1988-1994 compared to the last years of socialist management (by a factor of 1.3 to 1.8). Between 1994 and 2000, yearly disturbance rates declined markedly below pre-1990 values in all three countries (Figure III-4).

While the general disturbance trends of the three countries were comparable, we found distinct differences in the extent and the rate of disturbances. Annual disturbance rates were lowest in Poland (e.g., annual disturbance rates from 1994-2000 of only 0.05%). In Slovakia and Ukraine annual disturbance rates were higher by a factor of 2.3-4.5 (Figure III-4), and highest in Ukraine (up to 0.58%). In total, only 2.2% (55.5km²) of the forested area was affected in Poland compared to 6.2% (144.2km²) and 6.7% (310.6km²) in Slovakia and Ukraine, respectively (Figure III-4).

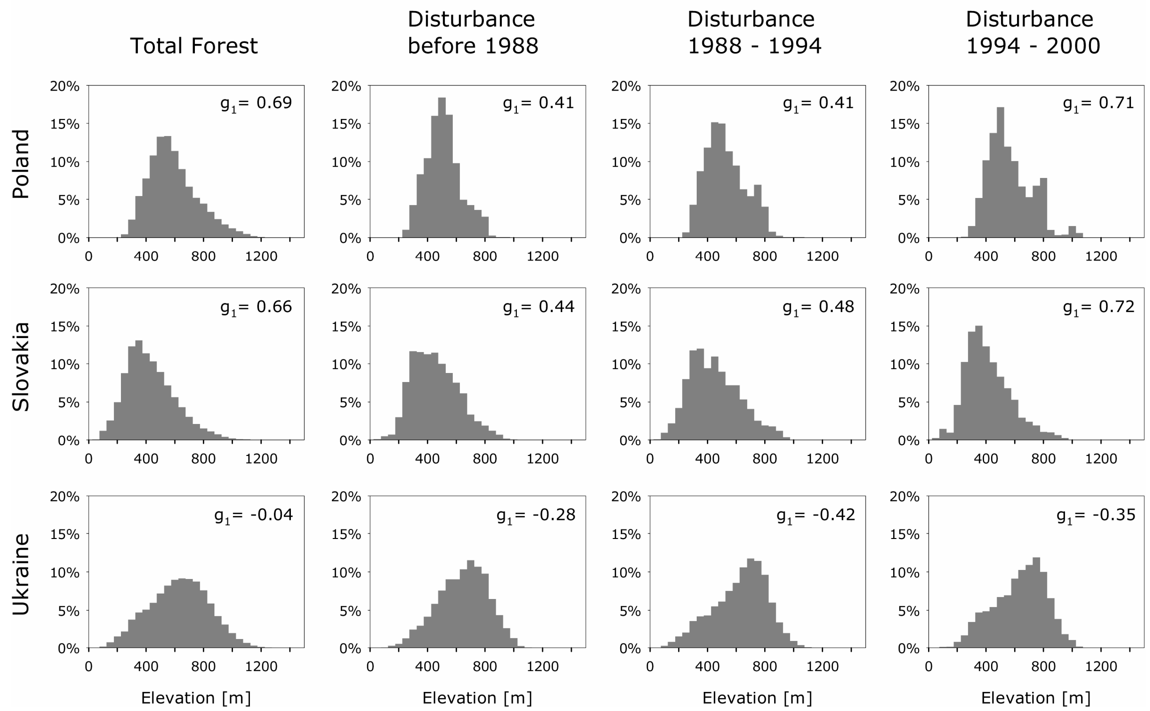

Figure III-5: Altitudinal distribution of total forest area (unchanged forest and disturbances) and disturbances for 1988, 1994, and 2000 for the three countries. (Distributions are normalized; g1 = skewness).

Most disturbances in Poland and Slovakia occurred in the foothill zone (below 600m), but the majority of disturbed forests in Ukraine occurred in the montane zone (between 600m and 1,100m) (Figure III-5). The distributions of disturbed forests differed markedly from the distribution of total forest (unchanged and disturbed forests), and elevational distributions remained constant over time. In Poland disturbance was relatively more common between 300 – 500m, and less common above 600m. In contrast, in Ukraine the disturbances were relatively more common at higher elevations. Only in Slovakia, were the elevational distributions of forests and disturbances similar (Figure III-5).

Ukraine had by far the most extensive disturbance in all time periods with area-weighted mean patch sizes of 4.8-9.3ha, which was 1.5-3 times bigger than in Poland or Slovakia (Figure III-3). Poland had the smallest disturbances, but area-weighted mean patch size increased from 1.7ha to 4.0ha in the 1990s. In Slovakia and Ukraine on the other hand, disturbances were larger in the 1988-1994 period (5.7ha and 9.3ha in area-weighted mean patch size, respectively) than in 1994-2000 (3.0ha and 4.9ha, respectively). Average disturbance size was always smaller than the area- weighted mean patch size, due to many small disturbances.

The stratification of disturbances into forest types had an overall accuracy of 82.4% and user's accuracies of 88%, 67%, and 88% for broad-leaved, mixed, and coniferous forest, respectively. In Poland and Slovakia, the majority of disturbances occurred in broad-leaved forest (up to 74% and 95% respectively). In Ukraine, the proportion of disturbed coniferous forests was much higher (up to 40% in 2000). Comparing the distributions of disturbed forests over time, Poland and Slovakia showed little variation, whereas the Ukrainian share of coniferous forests increased from 28% to 40% (Figure III-6).

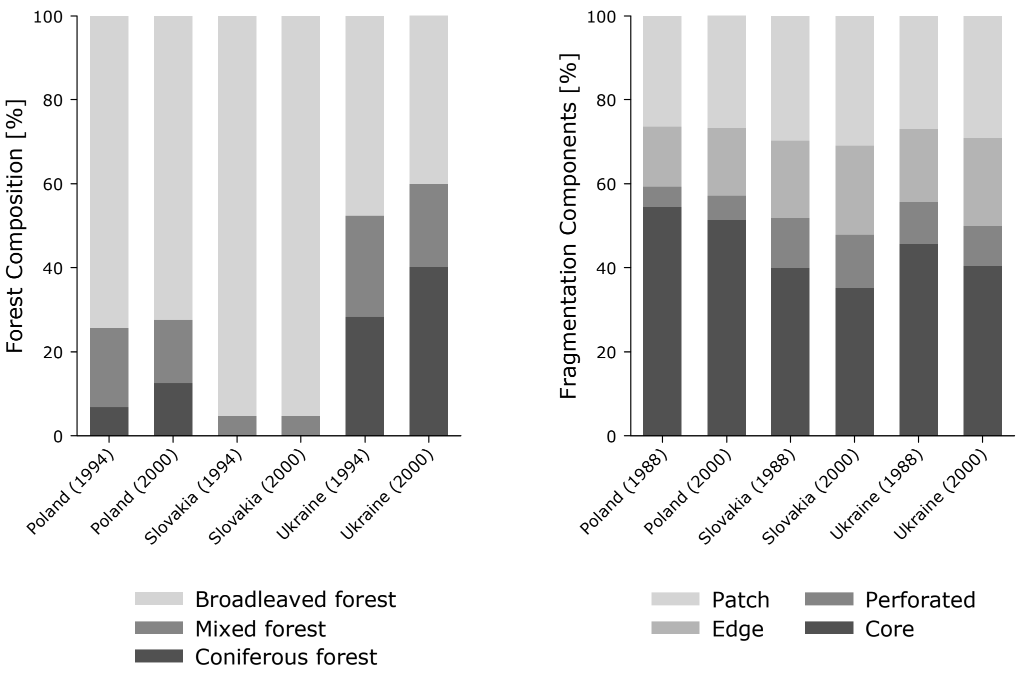

Figure III-6: Left: Distribution of disturbed forests among the forest types broad-leaved forest, mixed forest, and coniferous forest for disturbances mapped in 2000 and in 1994. Right: Forest fragmentation components for the years 1988 and 2000.

Higher disturbance rates in post-socialist times led to an increase in forest fragmentation in all three countries (Figure III-6). Core forest area decreased relatively little in Poland (2.9%) compared to Slovakia (4.8%) and Ukraine (5.2%), where losses in core forest were connected to an increase in edge forest (3.0% in Slovakia and 3.6% in Ukraine). Generally, Poland had much higher shares of core forest and low levels of perforated forest (less then 5%), while Slovakia showed the lowest rates of core forest and the highest shares of perforated and patch forest (Figure III-6).

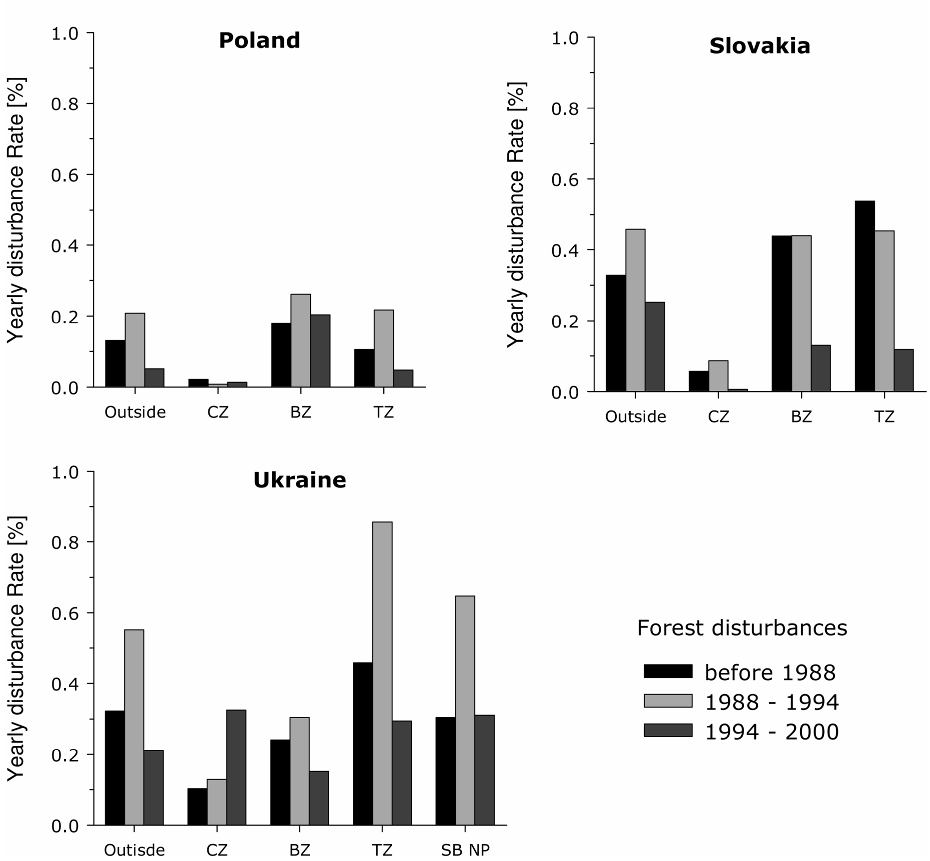

Figure III-7: Annual forest disturbance rates inside and outside protected areas per country and time period. Disturbance rates are given for the core zone (CZ), buffer zone (BZ), and transition zone (TZ) of the East Carpathian Biosphere Reserve, for the Skole Beskydy National Park (SK NP), and for areas outside of protected areas (Outside).

Protected areas exhibited generally lower forest disturbance rates than non-protected areas, but this response varied strongly in time and among countries (Figure III-7). Poland generally had less disturbance than the other two countries in all zones, and the core zone was almost undisturbed in all time periods (maximum annual disturbance rate of 0.02%). Disturbances in the buffer and transition zone were most frequent in 1988-1994, and it was surprising that annual disturbance rates in the buffer zone exceeded those outside protected areas (Figure III-7). In Slovakia, the core zone experienced much lower annual disturbance rates (up to 9 times lower) than all other zones. Forest disturbance rates in the buffer and transition zones were higher than those outside protected areas before 1988 (annual rates >0.4%), but did not increase from 1988-1994 (unlike disturbance rates outside protected areas). From 1994-2000, rates dropped markedly, well below the annual rate of disturbances outside parks (Figure III-7).

In Ukraine, all zones of the protected areas experienced relatively high disturbance rates and annual rates inside protected areas were not substantially lower than those outside parks (Figure III-7). Unlike Poland and Slovakia, disturbances in the core zone in Ukraine increased, particularly in 1994-2000. In the transition zone and in the Skole Beskydy National Park, annual rates roughly doubled in 1988-1994 and exceeded disturbance rates outside protected areas (reaching annual disturbance rates of 0.86% and 0.65%, respectively), but rates decreased in 1994-2000 (Figure III-7).

5 Discussion

5.1 Comparison of post-socialist forest disturbance rates among countries

Major changes in forest cover and forest fragmentation occurred in the border triangle of Poland, Slovakia, and Ukraine. Large-scale natural disturbances are rare in the study area and most disturbances detected in our analysis can therefore be attributed to logging. Harvesting rates were relatively moderate overall and are not necessarily unsustainable considering the average rotation age (> 100 years) in the region. However, the spatial pattern of disturbances revealed harvesting hotspots (e.g., the Skole region in Ukraine), where overexploitation likely occurs (Figure III-3). Trends in harvesting rates were similar in all three countries, and spiked markedly in the 1988-1994 period. We suggest that increasing rates are at least partially due to the fundamental changes in institutions, policies and economic conditions during the transition from socialist to post-socialist regimes.

Poland had the lowest harvesting rates among the three countries (Figure III-4) and low levels of forest fragmentation (Figure III-6). These patterns are likely due to forest management practices and socio-economic conditions. Timber harvesting is based on selective logging, which was already carried out before 1990 (Turnock 2002). Thus, although timber is being harvested, it leads to lower disturbance rates, because the canopy is only partly removed. Some areas in Poland were depopulated after World War II, resulting in a very low population density, lower local demand for forestry products, and lower anthropogenic pressure on forest resources (Augustyn 2004). After the system change (i.e., in 1988-1994), harvesting rates increased only moderately (Figures 4). This is likely due to the stable ownership situation, the policy framework, and the strength of institutions in Poland. Forests in the study area were almost entirely owned by the state in socialist times and ownership did not change substantially after 1990. Forest institutions were reformed relatively quickly (Polish Forestry Act 1991/97, Kissling-Naf and Bisang 2001), and forest management further improved toward sustainable forestry during the 1990s (Turnock 2002), which is reflected in an almost even age class distribution of Polish forests (Röhring 1999).

Slovakia differed markedly and showed higher harvesting rates (Figure III-4) and the highest forest fragmentation (Figure III-6), likely due to forest ownership, forest management policies, and harvesting practices. Forest ownership patterns changed after 1990, when 43% of forests were restituted to private owners (Eronen 1996; FAO 2005). The reform of forest management agencies and policies was slow (Kissling-Naf and Bisang 2001), partly due to the complex ownership situation (Eronen 1996). These factors, together with the economic depression in the early 1990s, likely led to increased forest harvesting for rapid profit realization (Eronen 1996; Webster et al. 2001; Turnock 2002). However, increased harvesting does not necessarily lead to unsustainable use of forest resources. Forest composition of much of Slovakia's forests is relatively natural (Oszlanyi 1997), and the age class distribution of Slovakia's forests is near-normal with a high proportion of mature forests (MASR 2003). Moreover, disturbance rates were overall relatively moderate, particularly when considering the high annual increment of up to 6m³ per hectare. Timber harvesting in Slovakia is largely based on clear-cutting, which led to higher levels of forest fragmentation and disturbance rates compared to Poland (Figure III-4).

In Ukraine, forest harvesting experienced the strongest increase in 1988-1994, but decreased below pre-1988 levels in 1994-2000 (Figure III-4). Forest ownership did not change after 1990 and all forests remained state owned (Turnock 2002). A new forest code toward more sustainable forestry was issued in 1994, but inadequate legislation and corruption resulted in a gap between policy and practice (Nijnik and Van Kooten 2000). After Ukraine became independent in 1991, administrative control decreased, but forest enterprises were still well equipped from Soviet times, funds were available, and the wood processing industry was still active, altogether explaining higher harvesting rates. However, the general economic situation grew increasingly worse, and many forest enterprises did not modernize and became poorly equipped and funded (Turnock 2002). The demand for timber and the output of the wood processing industry fell dramatically (for example -60% in sawnwood, -70% in particle board, Buksha et al. 2003) and both afforestation of farmland, and reforestation after forest harvesting practically ceased (Nijnik and Van Kooten 2000; Buksha 2004). The age class distribution was already skewed towards younger ages due to heavy exploitation in socialist times, and mature forest became increasingly scarce (Nijnik and Van Kooten 2000; FAO 2005), which may explain decreases in harvesting between 1994-2000. The shortage of mature forest (less than 12% of total forests (Strochinskii et al. 2001), is also an explanation for harvesting of coniferous stands and at higher altitudes. Timber harvesting in Ukraine is generally based on clear cuts using heavy machinery, thus explaining the bigger harvesting patches found there (Strochinskii et al. 2001).

Corruption and illegal forest harvesting in Ukraine increased during the transition phase and this trend may continue in the future (Nijnik and Van Kooten 2000; Buksha 2004; Nijnik and Van Kooten 2006). Poverty is a driver of illegal logging (e.g., fuel wood harvesting, Turnock 2002), but there is also a substantial underground business in forestry (Nijnik and Van Kooten 2006) with largely unsustainable forest management practices. This is particularly apparent in the large volumes of so-called sanitary felling (i.e., clear cuts of 'unhealthy' stands), which reached 51% of all harvests in the Skole forestry district (Figure III-3; inset 3) between 1999 and 2005 (Chaskovskyy, pers. comm.). New forest policies place limits on clear cuts of fir and beech forest on steep slopes, at higher altitudes, or in water protection zones, and envisage the increase of protected areas (Verkhovna Rada 2000a, b). It would be interesting to assess how these policy changes affected harvesting rates in Ukraine after 2000, however, this legislation does not effectively control sanitary felling practices.

Forest ownership pattern is important to understand forest cover change (Turner et al. 1996), but in our study area neither state forestry nor private forestry was clearly better in lowering harvest rates. Forests in both Poland and Ukraine are state owned, yet disturbance rates differed by a factor of 2.3-4.5. On the other hand, harvest rates in largely privately owned Slovak forests were almost as high as in Ukraine. We found the highest harvest rates in the transition phase (1988-1994) and rates decreased where economies stabilized and after sustainable forest policies were launched. Thus, our results rather support the assumption that the strength of institutions is important and that good institutions result in stable or even increasing forest cover (Dietz et al. 2003; Tucker and Ostrom 2005).

5.2 Forest disturbances inside and outside protected areas

The marked differences in protected area effectiveness are likely related to socio-economic conditions and strength of institutions. Protected area effectiveness was highest in Poland and Slovakia, whereas the establishment of protected areas in Ukraine lowered forest disturbance rates, yet, often not below harvest levels outside protected areas (Figure III-7).

Population density and poverty are drivers of anthropogenic forest disturbance (Lambin et al. 2001) and challenges for the effectiveness of protected areas (Naughton-Treves et al. 2005). In Poland, anthropogenic pressure on forest ecosystems is much lower compared to Slovakia and Ukraine, due to the depopulation of some areas in 1947. Harvest rates and forest fragmentation were very low (particularly in the core zone), and Poland had large continuous forest patches (Figure III-3). As a consequence, the highest densities of top carnivores and herbivores (e.g., wolf, brown bear, and European bison) are found in the Polish region of the study area (Perzanowski and Gula 2002). In Slovakia and Ukraine, population density is much higher and we found higher harvest rates inside protected areas (Figure III-7). However, the economic depression that occurred after 1990 lowered the effectiveness of protected areas in all three countries and forest harvesting increased from 1988-1994 within protected areas.

The designation of protected areas stops forest cover change in most cases (Bruner et al. 2001), even when institutions are weak (Naughton-Treves et al. 2005). This is supported by our results, because harvest rates dropped markedly in all countries after protected areas had been established (i.e., in 1994-2000). Yet, the strength of institutions is another important factor for the effectiveness of protected areas. Poland and Slovakia have strong institutions and were on the eve of EU accession in the late 1990s. After parks were designated, harvest rates dropped well below rates outside protected areas, especially in Slovakia (Figure III-7). In Ukraine, where governance is not transparent and corruption is a problem (Nijnik and Van Kooten 2006), harvesting rates inside protected areas did not decrease below those outside protected areas, and were sometimes even higher. The weakness of institutions and park management is also apparent in the enforcement of park regulations (Bruner et al. 2001; Webster et al. 2001). Forest harvesting has caused increasing fragmentation inside and around protected areas in the Carpathians, similar to other regions in the world (Chape et al. 2005; DeFries et al. 2005; Naughton-Treves et al. 2005), which is especially problematic for top carnivores and herbivores (Woodroffe and Ginsberg 1998).

The age of protected areas can be an important determinant of park effectiveness, because capacity building takes time. Protected areas in Slovakia, and particularly in Ukraine may be too young to draw final conclusions about the effectiveness of their park management. It is noteworthy though that forests in Ukraine and Slovakia were heavily exploited immediately prior to the designation of protected areas, likely at the expense of biodiversity rich older and near-natural forest in remote areas (Perzanowski and Szwagrzyk 2001). These fragmented large continuous forest patches and resulting edges effects may negatively affect forest biodiversity. Particularly in the Skole Beskydy National Park, where forest harvesting was concentrated (Figure III-3, inset 3), and field visits in 2006 confirmed that logging is ongoing.

5.3 Comparison of forest disturbance rates and official statistics

Comparing our forest disturbance trends to official forestry statistics reveals agreement in some cases, and clear differences in others. In Poland, the amount of timber harvested was relatively stable according to statistical records in the last socialist years (Strykowski et al. 1993), and increased markedly throughout the 1990s (FAO 2005). Timber harvest statistics in Slovakia indicate a decline in the late 1980s from around 5.8 million m^3 to less then 5 million m^3 between 1991-1993, but a considerable increase after 1993 to more than 6 mil m^3 in 2000 (Kolenka 1992; MASR 2003; FAO 2005). In Ukraine, harvesting trends are less clear. Some sources indicate decreasing harvesting in the 1990s (Nilsson and Shvidenko 1999; FAO 2005), yet, others show increased harvesting between 1986-1996 (Nijnik and Van Kooten 2000).

Several factors possibly explain differences between the statistics and the disturbance rates we derived from the remote sensing data. First, comparing harvested timber volumes (in m^3) and disturbed area is not easy, because these parameters are not necessarily connected. For instance, increasing average stand age results in higher annual increments and standing volumes, thus allowing for increased timber harvests without automatically increasing the logged area. This may particularly be the case where the age class distribution of forest stands shows a high percentage of premature and mature stands such as for example in Slovakia (MASR 2003), and where sustainable forestry is in place (thus leading to a steady increases in standing volume). Conversely, if average stand age gradually decreases due to premature logging, a decline in timber volume harvested may still lead to an increase in disturbed area. Premature logging may be especially common where the age class distribution is skewed towards younger stands (e.g., in Ukraine, Strochinskii et al. 2001) and where new forest owners decided to realize returns quickly (Turnock 2002).

Second, selective logging is not detected with our methodology, yet, is the dominant harvesting practice in Poland. This inhibits the comparison of harvested timber volumes to our disturbance map, because we defined disturbances as the complete removal of forest cover. Moreover, where forest management changes and selective logging becomes more common, for instance due to policies that emphasize sustainable forestry (Kissling-Naf and Bisang 2001), the comparison of disturbance rates and timber volumes is difficult. Third, official statistics do not account for illegal logging, which is a particular problem in Ukraine (Nijnik and Van Kooten 2000; Buksha 2004), thereby underestimating actual disturbance rates. And last, the disturbance index may overlook some types of forest harvesting (e.g., very small clear cuts). Although we cannot completely rule this out, our extensive accuracy assessment and field visits suggest a reliable forest disturbance map (see next section for details).

5.4 Accuracy of the forest disturbance detection

The disturbance index was so far only tested for three boreal study areas dominated by coniferous species (Healey et al. 2005). Our study was the first to apply the disturbance index to temperate forest ecosystems with mainly broad-leaved and mixed forest types. Overall, the disturbance index performed very well and the accuracy assessment confirmed an accurate change map.

The time interval between the images proved to be crucial for the successful mapping of forest disturbances. Due to the high productivity of Carpathian forests, vegetation regenerates quickly (particularly where reforestation is carried out) after a disturbance event. Thus, the disturbance index is most sensitive to relatively young disturbances, whereas the detection of older disturbances is difficult. The 1994 image was crucial in this respect, since many post-socialist disturbances could not have been detected using 1988 and 2000 data alone.

Although our accuracy assessment confirmed the reliability of our change map, a few factors were identified that may have contributed uncertainty. First, reforestation of clear cuts in Ukraine decreased dramatically after the system change (Buksha 2004). Later disturbances thus became easier to detect, because natural regeneration is slower. Disturbance rates from before 1988 may in such cases be underestimated. Second, the coarser spatial and spectral resolution of the MSS images compared to the TM/ETM+ data may have introduced uncertainty. However, it is important to note that the coarser-resolution data was only used to fill non-forest gaps in the initial TM-based forest/non-forest map. We included all non-forest patches smaller than 21 pixels (~1.9ha) in our change analysis, to avoid an underestimation of pre-1988 disturbance rates in areas where clear cuts were very small (e.g., in Slovakia). The change analysis was carried out using TM images only. The accuracy assessment, high-resolution images and field visits did not suggest a systematic bias in our change map.

Third, the assumption that disturbances occur within forest patches may exclude disturbances at the forest fringe. Although we can not completely rule out that some disturbances were omitted, visual examination of the Landsat images and additional high-resolution data showed that disturbances on the forest fringe were very rare, such that the effect seemed to be negligible. Fourth, phenological differences among the images may have affected disturbance detection. To accommodate for this, we did not apply uniform thresholds to determine changed areas, but used a composite classification, where phenological differences can be incorporated through appropriate training data for changed and unchanged areas. Nevertheless, phenology was a problem for some disturbances in 1988 that were spectrally similar to broad-leaved forest due to the late-summer image, and may have contributed to an underestimation of pre-1988 disturbance rates. Although differences in leaf onset in spring and defoliation in autumn may pose serious limitations when mapping forest disturbance of broad-leaved forests in mountain areas, this was not a problem in our case, because we did not rely on leaf-off images. Last, the exclusion of forest disturbances smaller than 7 pixels may have lead to an omission of some very small clear cuts, but we found that removing noise due to misclassifications had a much greater effect on the overall accuracy of the change map. The disturbance index was unable to detect selective logging, where only a fraction of the canopy is removed, yet, we were not interested in such disturbances. Mapping selective logging sites may be important in other studies and future research is needed to quantify the sensitivity of the disturbance index to detect selective logging.

To avoid an overly optimistic accuracy assessment, we used an equal sample for all classes (a random sample would place most control plots in stable forests, which are easiest to classify). Nevertheless, our accuracy assessment may be positively biased due to two factors. First, ground truth plots were only established in locally homogeneous areas (3x3 pixels) to minimize misregistration error and to facilitate ground labeling (Foody 2002). This avoids class boundaries and mixed pixels, which can cause misclassifications (Foody

2002). Second, some disturbance plots were directly digitized from the Landsat data. Such an approach is common (e.g., Healey et al. 2005) because large disturbances can easily be identified. However, very small disturbances that are also harder to classify may be missed. We suggest that such errors were distributed evenly throughout the study area and among time periods, and did not affect the general differences among countries and disturbance trends that we observed.

6 Conclusions

Forest disturbances were frequent in the border region of Poland, Slovakia, and Ukraine in post-socialist times, and most disturbances represent forest harvesting, because large-scale natural disturbance events are rare in the study area. Harvesting rates were generally relatively moderate, however rates increased in all three countries after the system change in 1990, leading to higher levels of forest fragmentation. The increase in forest harvesting likely occurred due to ownership changes, worsening economic conditions, and the weakening of institutions. Forest disturbance rates differed markedly among countries, with much lower rates in Poland compared to Slovakia and Ukraine. We suggest that these differences can be explained by differences in forest management practices, forest policies, and the strength of institutions.

Protected areas generally exhibited less forest harvesting, but protection was far from complete, and the effectiveness of protected areas differed among countries. Protected area management was most effective in Poland, where population density is low and protected areas are relatively old, and in Slovakia, where harvesting rates dropped markedly below background levels after protected areas were designated. In Ukraine, harvesting rates inside protected areas were practically equal to those outside, and harvests were widespread immediately before the designation of protected areas.

Overall, the Polish, Slovak, and Ukrainian region of our study area have clearly diverged in terms of forest cover and forest fragmentation in post-socialist times. Poland, where forest cover was highest and forest fragmentation lowest, had the lowest disturbance rates. Conversely, Slovakia and Ukraine, with lower forest cover and higher forest fragmentation, had higher disturbance rates. While the stand age distributions of Poland and Slovakia do not necessarily suggest unsustainable use of forest resources, increased harvesting is of particular concern in Ukraine, where mature forests have become scarce.

The strong differences in harvesting rates that we found among the countries Poland, Slovakia, and Ukraine were determined by broad-scale socio-economic factors, past and present forest management practices, forest policies, and the strength of institutions. Cross-border comparisons can reveal important insights into the role of broad-scale factors of human-environment interactions in forest ecosystems, and these factors may be equally important in other regions of the world.

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Chapter IV:
Cross-border comparison of post-socialist farmland abandonment in the Carpathians

Ecosystems. forthcoming

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Abstract

Agricultural areas are declining in many areas of the world, often because socio-economic and political changes make agriculture less profitable. The transition from centralized to market-oriented economies in Eastern Europe and the former Soviet Union after 1989 represented major economic and political changes, yet the resulting rates and spatial pattern of post-socialist farmland abandonment remain largely unknown. Remote sensing offers unique opportunities to map farmland abandonment, but automated assessments are challenging because phenology and crop types often vary substantially. We developed a change detection method based on Support Vector Machines (SVM) to map farmland abandonment in the border triangle of Poland, Slovakia, and Ukraine in the Carpathians from Landsat TM/ETM+ images from 1986, 1988, and 2000. Our SVM-based approach yielded an accurate change map (overall accuracy = 90.9%; kappa = 0.82), underpinning the potential of SVM to map complex land use change processes such as farmland abandonment. Farmland abandonment was widespread in the study area (16.1% of the farmland used in socialist times), likely due to decreasing profitability of agriculture after 1989. We also found substantial differences in abandonment among the countries (13.9% in Poland, 20.7% in Slovakia, and 13.3% in Ukraine), and between previously collectivized farmland and farmland that remained private during socialism in Poland. These differences are likely due to differences in socialist land ownership patterns, post-socialist land reform strategies, and rural population density.

1 Introduction

Human pressure is decreasing in many rural areas in the world due to urbanization, industrialization, and declining populations (Rudel 1998). These demographic changes often result in farmland abandonment, especially where farming conditions are marginal (Baldock et al. 1996; Ramankutty et al. 2002; Lepers et al. 2005). Abandoned farmlands may revert back to forests (Rudel et al. 2005) and this offers unique opportunities to restore some services of natural ecosystems, such as soil stability (Tasser et al. 2003) and water quality (Hunsaker and Levine 1995). Forest expansion on former farmland may also allow forest biodiversity to recover (Bowen et al. 2007), and may help mitigate climate change through increased carbon sequestration (Silver et al. 2000; Grau et al. 2004). Information about the rates and spatial pattern of abandoned farmland is thus important to assess its consequences for ecosystem services and biodiversity. Unfortunately, little is known about rates and spatial patterns of farmland abandonment, particularly outside Western Europe and North America.

Farmland abandonment is often triggered by changing socio-economics, institutions, and land management policies (Grau et al. 2004; DLG 2005; Yeloff and van Geel 2007). The economic and political transitions that occurred in Eastern Europe and the former Soviet Union after the fall of the Iron Curtain in 1989 is a prime example of this process. During socialism, all Eastern European countries collectivized farmland – albeit at different rates – and intensified agricultural production (Turnock 1998b; Lerman et al. 2004). Agriculture was heavily subsidized and production was mainly targeted at socialist markets. The situation changed drastically after 1989. Prices were liberalized and old markets diminished. New markets became accessible (e.g., the European Union), but there was also much stronger competition with foreign producers (Turnock 1998b; Trzeciak-Duval 1999). Most Eastern European countries carried out land reforms to restructure the farming sector, individualize land use, and privatize farmland (Swinnen et al. 1997; Lerman et al. 2004). However, former land owners were in many cases urban dwellers not interested in farming (Mathijs and Swinnen 1998; DLG 2005), and young people migrated to cities (Ioffe et al. 2004; Palang et al. 2006). Altogether, these processes resulted in widespread farmland abandonment across Eastern Europe in the post-socialist period (Bicik et al. 2001; Nikodemus et al. 2005; Müller and Sikor 2006). The problem is that while general trends in farmland abandonment are acknowledged, detailed information on these trends is lacking and the consequences of farmland abandonment on Eastern Europe's ecosystems remains poorly understood.

Quantifying farmland abandonment in Eastern Europe is not easy, because detailed agricultural census data are lacking or of unknown accuracy (Peterson and Aunap 1998; Filer and Hanousek 2002; DLG 2005). Remotely sensed data from before and after 1989 exists, but have rarely been used to study post-socialist farmland abandonment. Visual assessment of a Landsat image and historic maps revealed patterns of both farmland abandonment and agricultural intensification in southeast Poland (Angelstam et al. 2003). In Albania, a 7% cropland decline was found based on visual interpretation of Landsat images, and abandonment rates were highest in the first years of the transition (Müller and Sikor 2006; Müller and Munroe 2007). Aerial photo interpretation showed that 50% of the farmland used in socialist times had been abandoned in a Latvian study site by 1999 (Nikodemus et al. 2005). Only one study used automated change detection to map farmland abandonment for larger areas. In an assessment of Estonia's farmland, a rule-based classification of Landsat Multispectral Scanner (MSS) images revealed a 30% abandonment between 1990 and 1993 (Peterson and Aunap 1998).

The lack of automated assessments of farmland abandonment is not surprising, because most change detection methodologies are not well-suited to detect changes in land cover classes that are not spectrally stable (Coppin et al. 2004). In the case of agriculture, phenology and crop type variability may give false impressions of change, and multiple images for each time period are necessary to separate farmland in use from abandoned lands with high accuracy (Peterson and Aunap 1998; Oetter et al. 2001; Kuemmerle et al. 2006). Such multitemporal datasets can be analyzed by classifying all images simultaneously in a single change classification (Coppin et al. 2004). Change classes, however, are frequently characterized by complex distributions (e.g., multi-modal, non-normal) and many-to-one relationships (i.e., different crop types prior to abandonment all revert to one land cover type). Classifiers that do not assume specific class distributions, such as artificial neural networks (Benediktsson et al. 1990), or decision trees (Friedl and Brodley 1997) are most appropriate in such situations (Seto and Liu 2003). Recently developed support vector machine (SVM) classifiers have the additional advantage that they require only a relatively low number of training samples while performing equally well or better than other non-parametric approaches (Huang et al. 2002; Foody and Mathur 2004; Pal and Mather 2005). However, despite their potential advantages, SVM have to our knowledge not yet been used for automated land use change detection.

We developed an SVM-based method to map post-socialist farmland abandonment in Eastern Europe based on Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) satellite images. We focused on a study region in the Carpathian Mountains, because of the region's exceptional ecological value as biodiversity hotspot and Europe's largest temperate forest ecosystem (Webster et al. 2001). Farmland abandonment and forest expansion provide threats and opportunities for the region's biodiversity and ecosystems. For example, forest regrowth increases habitat availability and connectivity for forest dwelling species (Bowen et al. 2007), especially benefiting area-demanding top carnivores and herbivores that are still numerous in the Carpathians (Turnock 2002). Abandoned farmland could be afforested and the region may have considerable carbon sequestration potential (Nijnik and Van Kooten 2000). On the other hand, farmland abandonment threatens traditional cultural landscapes and their unique biodiversity (Cremene et al. 2005; Baur et al. 2006; Elbakidze and Angelstam 2007a). Despite the widespread effects of post-socialist farmland abandonment on ecosystems and biodiversity in the Carpathians, little is known about abandonment rates and spatial patterns.

Studying farmland abandonment in the Carpathians may also help understand the role of socio-economics, policies, and institutions for land use change. Such broad-scale factors are key for land use decisions (GLP 2005; Lambin and Geist 2006) and determine the profitability of farming (Baldock et al. 1996; MacDonald et al. 2000). However, little is known about their relative importance, because these factors are usually constant over times, or change only gradually, and they are often fairly uniform within a given study area. The rapid political and economic transition in Eastern Europe offers a unique "natural experiment" to study broad-scale determinants. Farmland abandonment may be among the largest land use changes in the European Union in the future (Verburg et al. 2006a) and assessing farmland abandonment in post-socialist Eastern Europe may reveal important insights into drivers of abandonment and its consequences for ecosystems. Studying rates and spatial patterns of farmland abandonment in border regions in the Carpathians is particularly interesting, because trans-boundary comparisons may reveal how differences in land management policies, land ownership, and institutional change affect abandonment (Kuemmerle et al. 2006). However, to our knowledge no study to date has compared rates and spatial patterns of post-socialist farmland abandonment among countries in Eastern Europe.

In summary, this study served two overarching goals: First, to use support vector machines (SVM) to map farmland abandonment in the Carpathian border region of Poland, Slovakia, and Ukraine based on Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) satellite images; and second to compare farmland abandonment among countries to better understand how socio-economic and institutional change affects land use change. Our specific objectives were:

(1) to develop a digital change detection approach based on multitemporal image classification using SVM;

(2) to quantify the extent, rates and spatial patterns farmland abandonment for our study area between 1988 and 2000;

(3) to compare farmland abandonment rates and spatial patterns among the three countries Poland, Slovakia, and Ukraine, and at different elevations and slopes; and to relate differences in farmland abandonment to differences in land reforms and socio-economic conditions between the countries.

2 Study Area

Our study area was the border triangle of Poland, Slovakia, and Ukraine in the Carpathian Mountains (Figure IV-1). We selected an area of 17,800km² based on administrative boundaries, landscape features such as rivers and valleys, as well as the extent of one Landsat TM scene (path/row 186/26). The region is characterized by mountainous terrain and altitudes vary from 200m to 1,480m above sea level. Carpathian flysh (sandstone and shale) is the main bedrock component (Denisiuk and Stoyko 2000), but some andesite-basalts are found in the southwest of the study area (Herenchuk 1968). Dominating soils include cambisols and podzols in the mountainous regions; podzoluvisols, greysems, and gleysols in the plains; and fluvisols in alluvial plains.

Climate in the study area is moderately cool and humid. Average annual precipitation amounts to 1,100-1,200mm, mean annual temperature is 5.9°C (at 300m), and the growing season ranges from >270 days below 500m altitude to <220 days above 800m (Zarzycki and Glowacinski 1970; Augustyn 2004). The potential natural vegetation can be stratified into three main altitudinal zones: A foothill zone (<600m) where broadleaved species dominate, particularly beech (*Fagus sylvatica*) and oak (*Quercus robur, Quercus petraea*); a montane zone (600-1,100m) with beech, silver fir (*Abies alba*), sycamore (*Acer pseudoplatanus*), and alder (*Alnus incana*); and alpine meadows with dwarfed beech (*Fagus sylvatica*) above the treeline (1,100-1,200m, Denisiuk and Stoyko 2000). Farming conditions vary in the study area and are relatively marginal in the montane zone (Dolishniy 1988; Turnock 2002). Dairy products, cattle, flax, oat, and potatoes are the main agricultural products here. In the foothill zone (including the plains in the north and south of the study area), farming conditions are more favorable, allowing to cultivate a diversity of crops, including grain (e.g., winter wheat, buckwheat), oil crops (e.g., rape, sunflowers), sugar beets, corn, and potatoes. Milk, cheese, and meat production are also significant agricultural activities in the foothill zone.

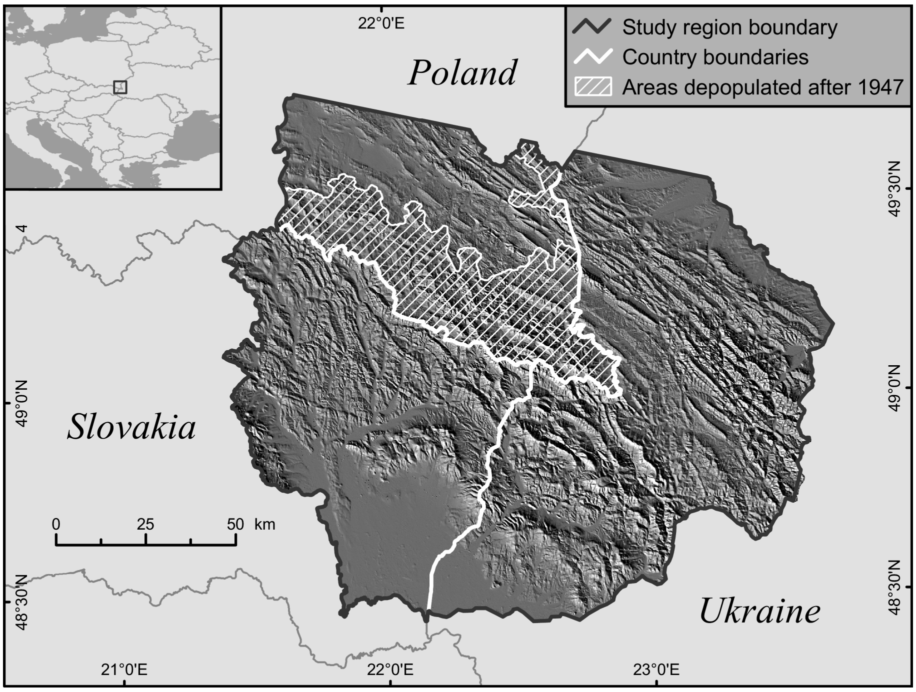

Figure IV-1: The border triangle of Poland, Slovakia, and Ukraine in the Carpathians. Farmland in the hatched region in Poland was mostly collectivized during socialism.

The region was part of the Austro-Hungarian Empire for a period of ~150 years until 1918. During that period, land use intensified markedly, mainly due to technological advancements and population growth (Turnock 2002; Augustyn 2004). The region’s forests were largely converted to farmland, particularly in mountain valleys and in the densely settled foothills and plains (Turnock 2002; Kozak et al. 2007), whereas forests remained dominant in the montane zone (> 60%, Kuemmerle et al. 2006). During socialist rule, great efforts were made to intensify agriculture in all three countries. However, land ownership and land management differed among the Polish, Slovak, and Ukrainian region of the study area. In Poland, most farmland was never collectivized (Lerman et al. 2004). Yet, many areas in the study area were owned and managed by the state, because these lands had been depopulated following border changes between the Soviet Union and Poland in 1947 (Figure IV-1), and large-scale farming enterprises were established in these areas (Turnock

2002; Augustyn 2004). In Slovakia, almost all farmland was collectivized and managed in state-controlled cooperatives, but land owners retained property rights to their fields (Lerman 1999; Csaki et al. 2003). This was different in Ukraine, where all land was owned by the state and managed in large-scale agricultural enterprises (collectives or state farms). After the demise of the Soviet Union, Slovakia, Poland, and Ukraine launched land reforms to privatize farmland and to individualize land use (Mathijs and Swinnen 1998). The land reform strategy largely depended on the land ownership pattern in socialist times, and thus differed among the three countries. Poland auctioned formerly state-owned farmland, Slovakia restituted farmland to previous owners, and Ukraine distributed farmland among the workers of the agricultural enterprises (Lerman et al. 2004). This makes the study area particularly well-suited for comparing rates and spatial patterns of farmland abandonment among countries, and for exploring how differences in land ownership and land reforms relate to differences in farmland abandonment.

3 Datasets Used and Methods

3.1 Datasets Used

To map farmland abandonment in the study area, we used Landsat TM and ETM+ images (path/row 186/26) from the last socialist years (2nd October 1986, 27th July 1988) and from 2000 (10th June, 20th August). We used two images per time period because initial tests suggested better separability of active and abandoned farmland compared to only using a single image (Kuemmerle et al. 2006). Thermal bands were not retained due to their coarser resolution. All images were geometrically rectified, corrected for relief displacement using the Space Shuttle Radar Topography Mission (SRTM, Slater et al. 2006) digital elevation model, and co-registered to the Universal Transverse Mercator (UTM) coordinate system (see Kuemmerle et al. 2006). Removing atmospheric influence and illumination variations due to topography improves change detection accuracy (Song et al. 2001) and we transferred all images to surface reflectance using a 5S radiative transfer model that incorporated a terrain-dependent illumination correction (Hill and Mehl 2003b). All forests (in 1988), water bodies, and built-up areas were masked out based on earlier classifications (Kuemmerle et al. 2006; Kuemmerle et al. 2007a). The 1988 image contained some clouds (<0.01% of the study area) which we excluded from the analysis. We also masked areas above 1000m altitude, because farming is not carried out at these altitudes in the study area. In total, 56% of the study area was masked. The four masked images were stacked into one multitemporal dataset.

Ground-truth points for training and validation purposes were collected in the field and from high-resolution satellite images. Field mapping was carried out in the summer of 2004, spring of 2005, and spring of 2006 using non-differential Global Positioning System (GPS) receivers. We considered only locally homogeneous areas (i.e., 90×90m or 3×3 Landsat pixels) to rule out erroneous assignments due to positional uncertainty. To cover wide areas, we photo-documented some sites (e.g., remote valleys) from view points (e.g., mountain ridges). View points were georeferenced, and the view angle and distance of the area depicted in the photo were registered. Thus, we were able to digitize ground-truth points on screen using topographic maps, high-resolution images, and the Landsat images as reference maps (Kuemmerle et al. 2006; Kuemmerle et al. 2007a). We also digitized additional ground truth points from sixteen Quickbird images available in Google Earth™ (http://earth.google.com) for the Slovak and Ukrainian region of our study area, and we obtained three IKONOS images for the Polish region. All high-resolution images were acquired between 2003 and 2005 and had a spatial resolution of 1m or finer. Ground truth points were digitized on screen using the same criteria that were applied in the field and photo mapping.

We categorized all ground truth plots into the classes 'unchanged areas', 'fallow land', and 'reforestation'. A field was considered fallow land if crops or managed grasslands (i.e., cut or intensively grazed) had been replaced by unmanaged grasslands or successional shrubland. Reforestation denotes the natural or artificial reestablishment of forest cover in areas that had been converted to some other land use (EEA 2007). Thus, the class 'reforestation' included all areas used for farming in 1986 and 1988 (crops and managed grassland) that had a closed forest canopy by 2000. Abandoned farmland was defined as the sum of fallow land and reforestation. Due to the time span between Landsat image acquisition (1986-2000), field campaigns (2004–2006), and high-resolution imagery (2003-2005) we determined the approximate time of abandonment based on the estimated age of successional shrubs, questioning of local farmers, and visual assessment of the Landsat images. We labeled all locations where abandonment occurred after 2000 as unchanged. Field visits and visual assessment of the Landsat images suggest no conversions from forests or fallow land to cropland between 1986 and 2000. In total, we gathered 1,652 ground truth points (481 based on ground visits and 1,171 from high-resolution remote sensing data).

3.2 Mapping farmland abandonment using SVM change detection

Image classifications with support vector machines (SVM) discriminate classes by fitting separating hyperplanes in the feature space based on training samples (Huang et al. 2002; Foody and Mathur 2004). The hyperplane that best discriminates two classes is constructed by maximizing the distance between the hyperplane and the closest training samples – the so-called support vectors (Burges 1998; Pal and Mather 2006). Thus, SVM use only training samples that characterize class boundaries and perform well with a relatively small number of training samples (Foody and Mathur 2006). For classes that are linearly not separable, a kernel function is used to transform training data into a higher dimensional space where a separating linear hyperplane can be fitted (Huang et al. 2002; Pal and Mather 2005). This allows SVM to handle complex class distributions and SVM should therefore be well-suited for separating classes in a multitemporal feature space. SVM were originally developed for binary classification problems and two main strategies exist to extend the approach to multi-class problems (Huang et al., 2002, Foody & Mathur, 2004). The one-against-one strategy applies a set of individual classifiers to all possible class pairs and performs a majority vote to assign the winning class. The one-against-all strategy uses binary classifiers to separate each class from the rest and the final class label is determined by the maximum decision value, i.e. the distance to the hyperplane (Huang et al. 2002). Both strategies result in comparable classifications (Melgani and Bruzzone 2004).

We used a one-against-all strategy to fit SVM for mapping farmland abandonment in our study area, because it is the simpler and more commonly used strategy. Two thirds of the ground truth points (1,079 points) were randomly selected to be used in the training phase of the SVM. Successful SVM training requires inclusion of pixels at the class boundaries (Foody and Mathur 2006). To account for this, we established buffer zones with a 45m (1.5 Landsat TM/ETM+ pixels) radius around the 1,079 training point locations and included all pixels with >50% area inside these buffers. Such a sampling strategy is efficient for selecting a sufficiently large training set while ensuring the inclusion of boundary pixels (i.e., mixed pixels) that are important for delineating the separating hyperplanes (Foody and Mathur 2006). In total, we used 7,789 training pixels based on 1,079 ground truth locations: 5,100 pixels (704 points) for unchanged areas, 2,332 (326) for fallow land, and 357 (49) for afforested areas.

A Gaussian kernel function was used to construct the three hyperplanes to separate each of the change classes from all other training samples (one-against-all). The Gaussian kernel function requires two parameters: γ controlling the kernel width, and C determining the magnitude of penalty given to misclassified training samples. To find the best parameter set for each hyperplane and to avoid overfitting, we systematically tested a wide range of γ and C combinations and compared them based on cross-validation errors. Once optimal parameters were found for all binary problems, we used the resulting SVM to classify the multitemporal stack of four images and to derive a map of farmland abandonment for our study area. To eliminate isolated pixels likely representing misclassifications (i.e., salt-and-pepper effect common to pixel-based classifications), we applied a 3x3 majority filter and assigned all patches smaller than 0.63ha (7 pixels) to the surrounding dominant class. The accuracy of the farmland abandonment map was based on the remaining 573 ground truth samples not used in the training of the SVM. We calculated an error matrix, overall and class-specific classification accuracies, and the kappa value (Foody 2002). SVM training (including kernel function parameter estimation), classification, and accuracy assessment were carried out with imageSVM (Janz et al. 2007).

3.3 Cross-border comparison of farmland abandonment

Based on the change map, we summarized the area of farmland abandonment (i.e., sum of fallow farmland and reforestation) for each country. To calculate abandonment rates, we divided the sum of fallow land and afforested areas by the total unmasked area. We also calculated reforestation rates separately for each country. To assess whether farmland abandonment varied along the altitudinal gradient in the study area, the DEM was categorized into 50m-wide elevation classes and we calculated fallow land and reforestation rates for each country. We also calculated the slope from the DEM (in percent; 100% = 45 degrees) and summarized abandonment rates for 20 slope classes defined using 5% breaks. In addition, we separated in Poland farmland that had been collectivized and farmland that was privately owned and managed in socialist times (Figure IV-1). To assess whether farmland abandonment differed, we calculated abandonment and reforestation rates for each farmland type. We determined the boundary between state-owned and private farmland under consideration of topographic maps that included the locations of former state farms (scale: 1:50,000) and in collaboration with a local historian (M. Augustyn, pers. comm.).

To assess the spatial pattern of farmland abandonment we calculated landscape indices (O'Neill et al. 1988b; Turner and Gardner 1991). We derived mean patch size, area-weighted mean patch size, and patch density for the classes fallow land and reforestation. The area-weighted mean patch size equals the sum across all patch areas while weighting each patch according to its relative abundance in the class (McGarigal 1994). Patch density was calculated as the number of patches per square kilometer of all unmasked areas. To assess the level of spatial aggregation of abandoned farmland patches, we also derived the aggregation index (*AI*) for both abandonment classes. The aggregation index assumes that pixels in a class with the highest level of aggregation ($AI = 1$) share the maximum number of possible edges (i.e. the class is clumped into a single compact patch). A class whose pixels share no edges is completely disaggregated ($AI = 0$) (McGarigal 1994).

4 Results

The change detection approach based on multitemporal image classification using support vector machines resulted in a farmland abandonment map with an overall accuracy of 90.9% and a kappa of 0.82. Unchanged areas had highest producer's and user's accuracies, while accuracies were slightly lower for the fallow land and reforestation classes (Table IV-1). Classification uncertainty was mainly due to confusion between unchanged areas and one of the two change classes, whereas confusion among fallow land and reforestation was negligible. Post-classification image processing (i.e., majority filter, and the removal of small patches) increased overall accuracy by 3.1%.

Table IV-1: Accuracy assessment of the change classification.

		Reference data				
		unchanged areas	fallow farmland	afforestation	Σ	user's accuracy [%]
Classified data	unchanged areas	349	19	4	372	93.82
	fallow farmland	24	136	1	161	84.47
	afforestation	3	1	36	40	90.00
	Σ	376	156	41	573	
	producer's accuracy [%]	92.82	87.18	87.80		

Farmland abandonment was widespread in the border triangle of Poland, Slovakia, and Ukraine between 1988 and 2000 (Figure IV-2). In total, 16.1% (1,285km²) of the farmland in socialist times was abandoned after the system change (i.e., the sum of fallow land and afforested areas) and 12.5% (161km²) of the abandoned farmland had already reverted back to forests. Abandoned fields were not distributed uniformly across the study area and showed a highly clustered pattern, particularly in the plains in the south of the study area and in some mountain valleys (Figure IV-2).

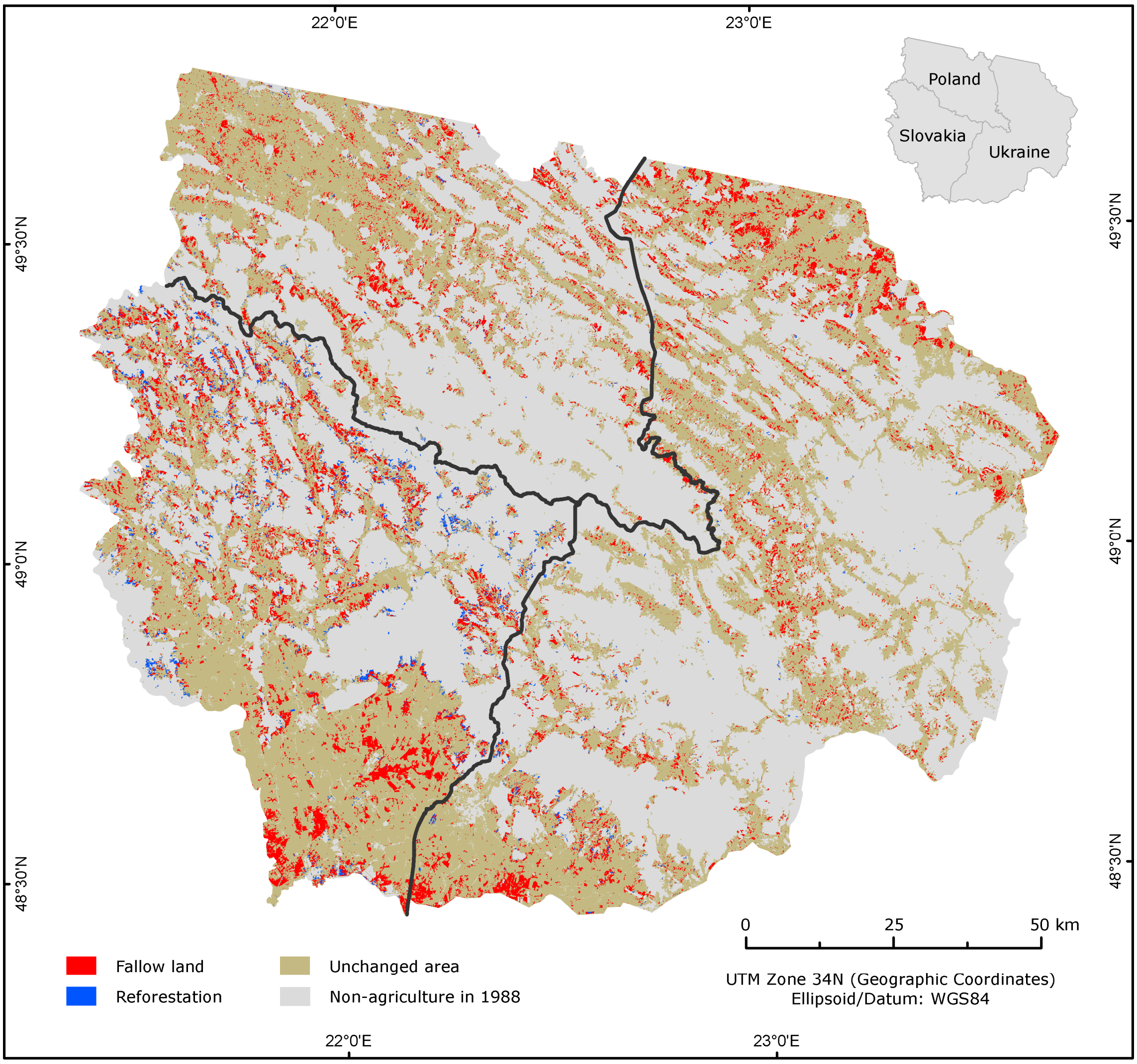

Figure IV-2: Farmland abandonment from 1986 to 2000 in the study area.

The change map revealed substantial differences in the rates and spatial pattern of post-socialist farmland abandonment among the Polish, Slovak, and Ukrainian regions of the study area. In Poland, 13.9% (sum of fallow land and afforested areas) of the farmland used in 1988 was abandoned by 2000 (240km², Figure IV-3). Abandoned lands were concentrated in the valleys along the Polish-Slovak and the Polish-Ukrainian border (Figure IV-2), although some clusters of abandoned fields also occurred in the north-western plain. Highest abandonment rates were found at altitudes between 350-550m (Figure IV-4) and where intermediate slopes prevailed (Figure IV-5), while abandonment rates were lower in the plains and in altitudes above 700m. Reforestation was not extensive in Poland, overall accounting for only 1.0% of the former farmland (17km²). Most reforestation occurred in mountain valleys at intermediate altitudes between 350-550m (Figure IV-4), and at steeper slopes (Figure IV-5).

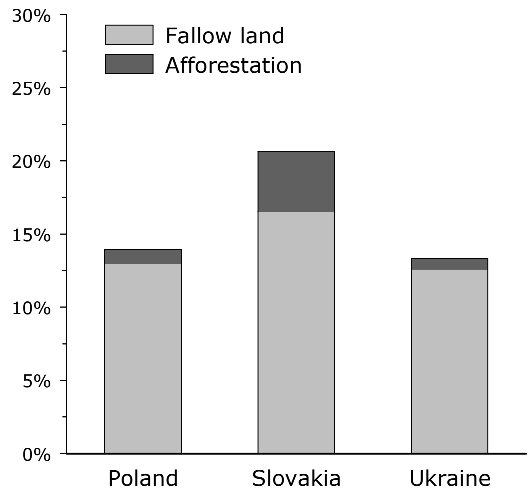

Figure IV-3: Comparison of fallow land and reforestation rates (1986/88 – 2000) among the Polish, Slovak, and Ukrainian portions of the study area.

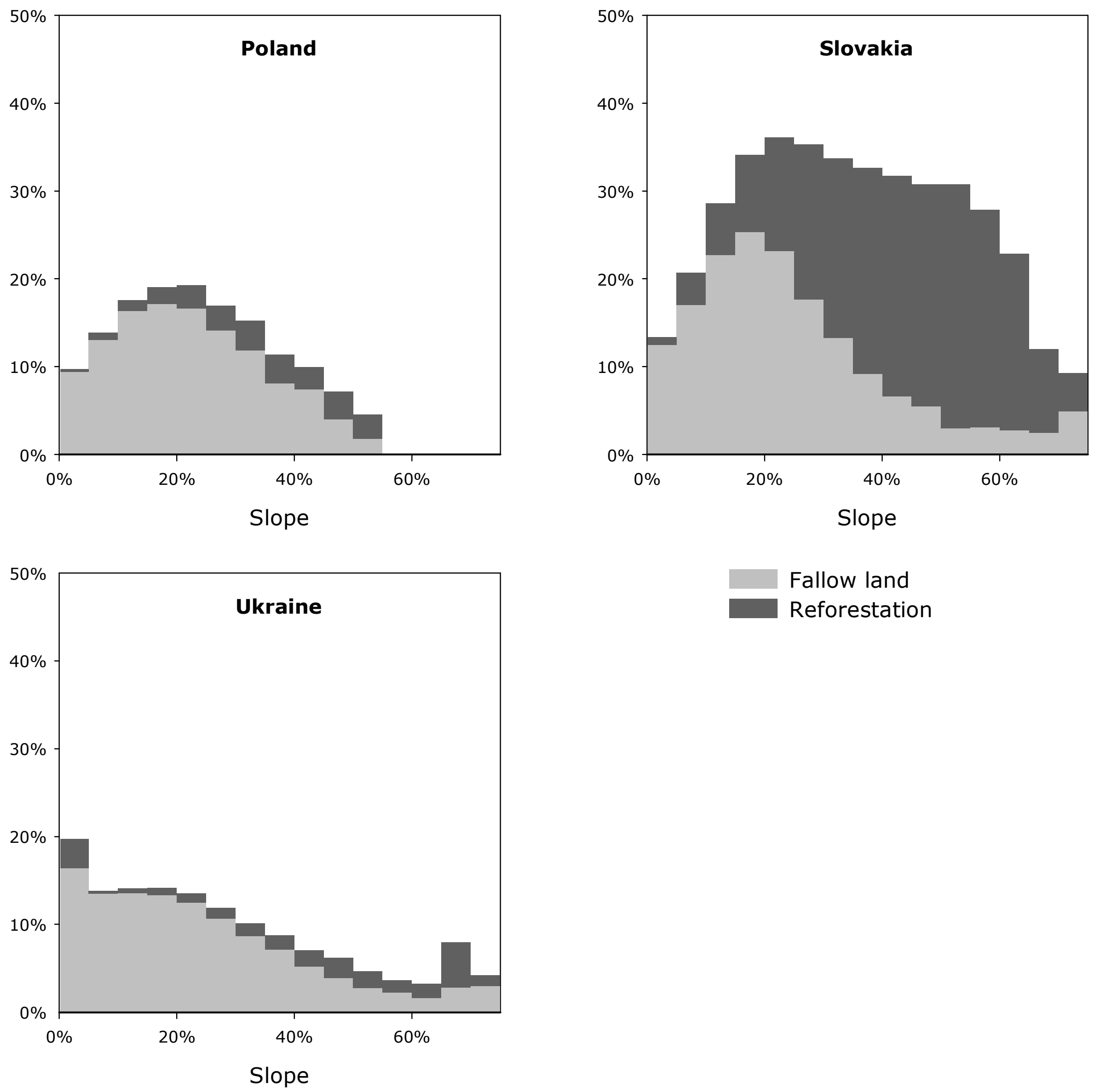

Figure IV-4: Rates of fallow land and reforestation (1986/88 – 2000) by elevation class (50m elevation increase per class, histogram bars are stacked).

We found marked differences in abandonment rates on farmland managed by large-scale farming organizations during socialism, and farmland that had always been owned and managed by private farmers. Abandonment rates were two-times higher on former state-owned land (21.8% versus 10.8%) and reforestation was more widespread where land had been collectivized (Figure IV-6).

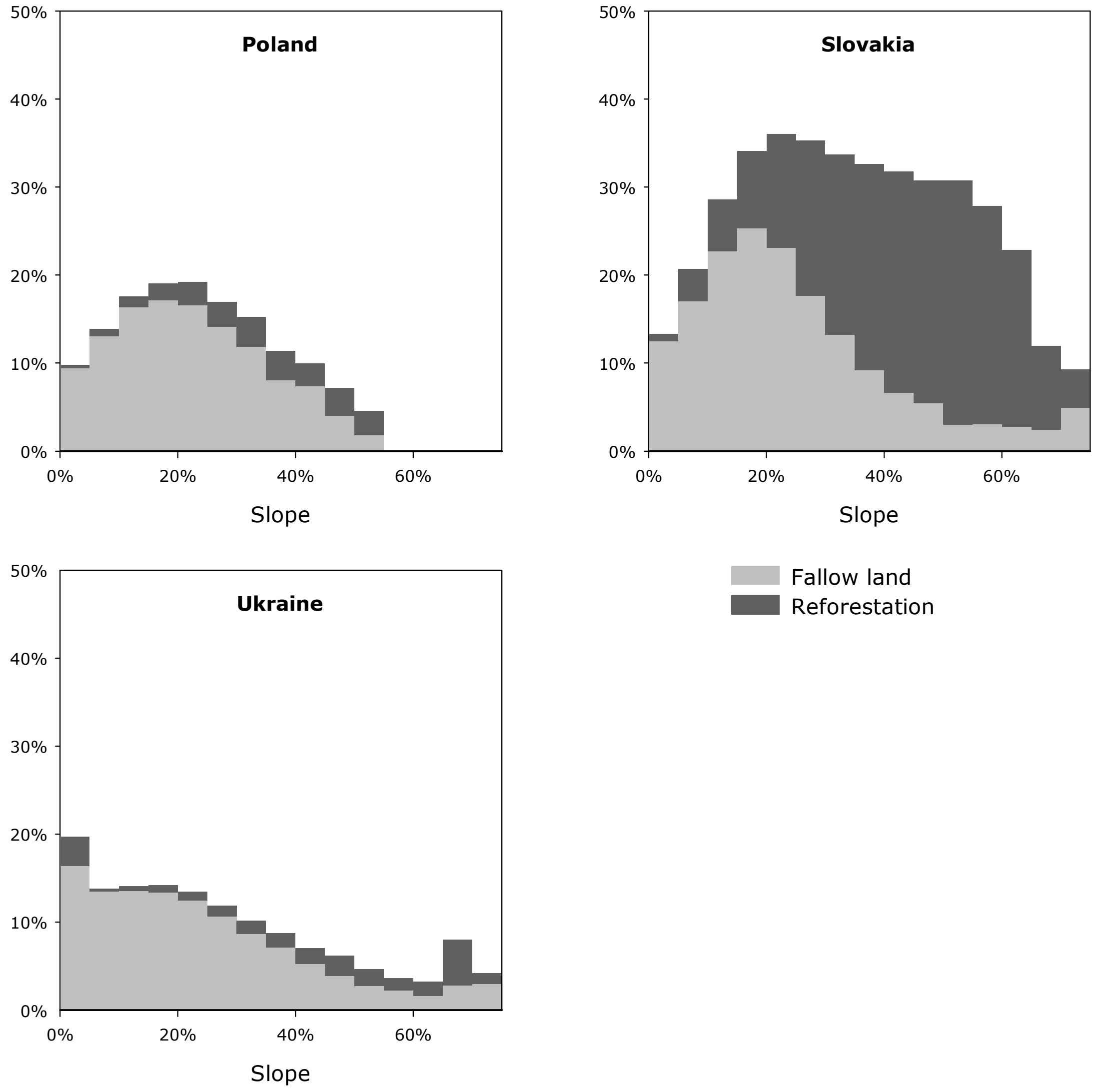

Figure IV-5: Rates of fallow land and reforestation (1986/88 – 2000) by slope class (5% slope per class; histogram bars are stacked).

Farmland abandonment was most extensive in Slovakia among the three countries in our study area with an overall abandonment rate (i.e., the combination of fallow land and afforested areas) of 20.7% (590km², Figure IV-3). Slovakia contained almost 46% of all abandoned lands in the study area. The spatial pattern of farmland abandonment in Slovakia was highly heterogeneous and characterized by some very large patches of fallow land in the southern plains as well as a high number of abandoned fields (fallow or afforested) in mountainous areas (Figure IV-2). Farmland abandonment rates were lower at lower altitudes and increased with elevation, exceeding 40% at 350-450m. Abandonment rates in Slovakia were higher than in Poland and Ukraine at all altitudes (Figure IV-4). Reforestation was extensive in Slovakia, covering 20.2% (119km²) of all abandoned lands, exceeding Polish and Ukrainian rates by a factor of 4.3 and 5.7, respectively. Conversion of farmland to forests was especially widespread in mountain valleys (~80% of all afforested areas occurred between 200m and 500m elevation) and reforestation rates were particularly high at higher altitudes (up to 80% at elevations above 700m). Whereas the rates of fallow lands were highest at intermediate slopes, reforestation occurred dominantly at steeper slopes (Figure IV-5) and at the forest fringe (Figure IV-2).

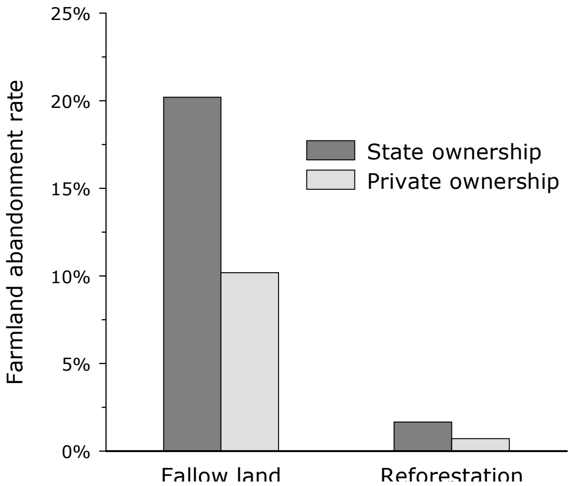

Figure IV-6: Comparison of farmland abandonment rates (1986/88 – 2000) of lands managed by the state during socialism and lands that were never collectivized in the Polish region of the study area.

In Ukraine, 13.3% (fallow land and reforestation) of all unmasked areas were abandoned between 1988 and 2000 (455km²). Abandonment patches were highly clustered in the plains in the north and south of the study area, whereas abandonment was more dispersed in mountainous areas (Figure IV-2). Thus, the location and spatial pattern of farmland abandoned differed considerably among the Polish and Ukrainian region of the study area although both countries had similar abandonment rates. Moreover, abandonment rates in Ukraine did not vary substantially with altitude unlike in Poland and Slovakia. We found higher rates at lower elevations and 50% of all abandoned land was located at altitudes below 350m. However, abandonment rates decreased only slightly with altitude and abandonment was still substantial at altitudes above 750m (Figure IV-4). In contrast to Poland and Slovakia, the highest abandonment rates occurred on gentle slopes (Figure IV-5). Among the three countries, reforestation was lowest in Ukraine (0.7%, Figure IV-3), mostly at lower altitudes (<200m) and above 750m elevation (Figure IV-4).

The size and the spatial pattern of abandoned patches also differed among the three countries (Table IV-2). Patches of fallow land were on average larger in Slovakia compared to Poland and Ukraine. The same was true for afforested areas: the area-weighted mean patch size for Slovak reforestation patches was up to a factor of 6.7 larger. Patch density of fallow lands was highest in Ukraine (1.4 times higher than in Poland and Slovakia), whereas the density of reforestation patches was 3.6 times higher in Slovakia than in Poland and Ukraine. Abandoned patches tended to be spatially aggregated, with aggregation index values of >0.8 for fallow land and approximately 0.7 for afforested areas. Patches of fallow land were slightly more clustered in Slovakia (AI = 0.85) compared to Poland (AI = 0.79) and Ukraine (AI = 0.82), and fallow land was characterized by a higher spatial aggregation than afforested areas.

Table IV-2: Mean patch size (Mean), area-weighted mean patch size (AMean), patch density (PD), and aggregation index (AI) for the fallow farmland and reforestation classes of the Polish, Slovak, and Ukrainian region of the study area.

	Mean	AMean	PD	AI
Fallow farmland (Poland)	3.79	26.53	1.42	78.92
Fallow farmland (Slovakia)	7.78	178.73	1.16	84.78
Fallow farmland (Ukraine)	4.95	124.65	1.07	81.84
Reforestation (Poland)	1.51	2.98	0.27	67.39
Reforestation (Slovakia)	2.90	11.85	0.78	75.22
Reforestation (Ukraine)	2.13	5.40	0.14	72.93

5 Discussion

5.1 Mapping farmland abandonment using SVM

To our knowledge, this is the first study that used support vector machines for land use change detection. The SVM separated active and abandoned farmland with high accuracy and were well-suited to handle complex multitemporal many-to-one classes (i.e., when different types of cropland were abandoned and all reverted to forests), which would have been difficult using parametric classifiers (e.g., maximum likelihood, Seto and Liu 2003). The relatively low number of training samples required, and inclusion of multiple pixels per location as training data were strong advantages of the SVM. Classification with other (parametric or non-parametric) classifiers would have required gathering substantially more training data and splitting complex change classes into many sub-classes. The SVM was also successful in separating managed and unmanaged grasslands, which is crucial for accurately mapping land abandonment, yet, can be difficult using traditional approaches (Peterson and Aunap 1998).

Overall, classification accuracy was high, some classification errors remain, and there may be several reasons for those. First, there was a time lag between Landsat image acquisition and ground truth collected in the field and from very high resolution images. Cross-checking all ground truth points with Landsat data was helpful (e.g., where farmland abandonment occurred after 2000), but we cannot rule out mislabeled ground truth points. Second, the minimum mapping unit of 7 pixels may have omitted small abandoned fields, even though this threshold removed noise due to misclassifications and thus improved the overall accuracy. Third and last, defining abandonment in itself is not easy (DLG 2005). We considered a field abandoned if intensive management during socialism (cropping, mowing, or high grazing pressure) ceased after 1990. Thus, our analysis cannot separate fully abandoned lands from areas used for occasional grazing or areas that lie fallow within a crop rotation cycle. However, extensive field visits and expert interviews between 2004 and 2006 confirmed that most fallow land in the study region was permanently abandoned and low-intensity grazing was only carried out in a few areas, suggesting that abandonment rates were not positively biased.

5.2 Farmland abandonment in the border region of Poland, Slovakia, and Ukraine

Farmland abandonment was extensive in our study area. We suggest this is mainly due to three factors: declining profitability of agriculture under free markets, restructuring of the agricultural sector, and societal change in Eastern Europe's rural landscapes. Whereas the first factor likely had a strong effect on farmland abandonment in all three countries that we studied, differences in land reforms and rural populations (factors 2 and 3) likely explain differences in post-socialist farmland abandonment rates among countries.

In socialist times, agricultural intensification and farmland expansion occurred even in marginal areas (e.g., characterized by steep slopes, or limited market access) thanks to subsidies and capital investment by the state (Turnock 1998b; Ramankutty et al. 2002). State support diminished after the breakdown of the Soviet Union, prizes were no longer fixed, and export markets in other socialist countries disappeared. Many Eastern European farmers were not able to compete under these conditions. Altogether, this decreased the profitability of agriculture substantially, particularly in marginal regions such as the Carpathians (DLG 2005) and resulted in a steep decline in agricultural production in the early 1990s (on average 31% in Eastern Europe, Trzeciak-Duval 1999). In our study area, conditions for farming are best in the plains and worst in the mountains (e.g., access to markets, terrain ruggedness, etc.). Abandonment rates reflected this gradient, particularly in Poland and Slovakia (Figure IV-4, Figure IV-5), and abandoned patches were highly clustered (Table IV-2). Similar to other European mountain regions, post-socialist farmland abandonment in our study area was connected to topography (Poyatos et al. 2003; Gellrich et al. 2007; Tasser et al. 2007). Yet, the rapid and extensive abandonment that occurred right after the system change (>16% in a period of only 12 years) emphasizes that socio-economic conditions are powerful determinants of land use marginality (Baldock et al. 1996; Grau et al. 2004).

The rates and spatial pattern of farmland abandonment differed substantially among the Polish, Slovak, and Ukrainian regions of our study area. These differences can not be solely explained by differences in the marginality of farming, because the region is environmentally relatively homogenous and the three countries faced similar economic challenges in the transition period. Instead, differences among countries appear to be most strongly related to differences in land ownership patterns, land reform strategies, and societal developments (e.g., rural population density and emigration).

In Poland, abandonment rates were twice as high on former state-owned land compared to collectivized land. State farms were only established in mountain valleys that had been depopulated after 1947 (Turnock 2002) and these areas have still a very low population density (e.g., 22 persons/km² in the Bieszczady County in 2000, SOR 2002). When Poland chose to auction off former state land after the system change, some farmland was acquired by the Polish Forest Service, but most was purchased by investors for speculative purposes rather than by local farmers. As a result, farmland in these areas was almost completely set-aside (Augustyn 2004), explaining the high abandonment and reforestation rates at intermediate altitudes and slopes, and the large clusters of abandoned lands we found in mountain valleys. The situation was different for private farmland. In these areas, population density is relatively high and economic difficulties and high unemployment in the early 1990s forced many people into farming (Gorz and Kurek 1998). Abandonment rates were lowest in these areas (Figure IV-6), the spatial pattern of abandonment was highly dispersed (e.g., lowest aggregation index and highest patch density among the three countries), and abandoned patches were smallest (Table IV-2 and Figure IV-2). We therefore suggest that abandonment in these areas was not triggered by increased land use marginality, but can be attributed to societal changes in the transition period (e.g., aging of rural populations, Gorz and Kurek 1998; SOR 2002; Palang et al. 2006).

High abandonment rates in Slovakia (Figure IV-3) can largely be attributed to the slow pace of land privatization and farm restructuring (Csaki et al. 2003). Slovakia restituted all farmland (Lerman et al. 2004). Yet, land tenure is highly fragmented, identifying former owners often proved difficult, and many of them were not interested in farming anymore, resulting in much unclaimed farmland (Mathijs and Swinnen 1998; van Dijk 2003; DLG 2005). This led to a two-fold pattern of farmland abandonment. In the plains, owners leased their land to large-scale farming organizations and the socialist farming structure largely survived (Csaki et al. 2003; Lerman et al. 2004). Abandonment was mainly clustered in areas of poor farming conditions, for example in marshlands (Figure IV-2). Farmland abandonment rates were higher in Slovak mountain valleys where production is limited by environmental conditions (e.g., at high altitudes, steep slopes, etc.) and where considerable emigration to urban areas occurred in the post-socialist period (Izakovicova and Oszlany 2007). The two-fold concentration of abandonment (i.e., in mountain valleys and along floodplains) also explains the high level of aggregation and the larger size of abandonment patches we found in Slovakia. Reforestation was especially widespread in protected areas that were established in the post-socialist period (Kuemmerle et al. 2007a) and around the Starina water reservoir, which was constructed in the late 1980s.

In Ukraine, many state-owned agricultural enterprises were not able to operate under market conditions and went bankrupt after 1989 (Ash and Wegren 1998; Augustyn 2004). Farmland was distributed among the workers of the former agricultural enterprises, but they lacked funds and machines, and a functioning land market did not exist until 2005 (Lerman et al. 2004). Altogether, this explains the high farmland abandonment rates in Ukraine. As in Slovakia, abandonment patches were highly clustered (Table IV-2) especially in areas with high ground water tables and less fertile soils, for example, in the northeastern foothill zone where podzols and gleysols dominate, or in the alluvial plain of the Tisza river in the southwest (Figure IV-2). Farmland abandonment was almost absent in the vicinity of larger settlements, but abandoned areas were widespread in the foothill zone. Farmland abandonment rates in Ukrainian mountain valleys did not differ substantially from rates in the plains and were sometimes even lower (Figure IV-4). In contrast to Polish and Slovak mountain valleys, rural population density is high in Ukrainian valleys (e.g., 2.8 times higher in Lviv Oblast compared to the Polish Bieszczady County, SOR 2002), and many people depend on subsistence farming. Despite difficult farming conditions much former state land was converted to household plots in the mountains, thereby explaining the absence of an elevation gradient in farmland abandonment and decreasing abandonment rates with increasing slopes. Some abandonment occurred where livestock farms operated in socialist times, because most animals were slaughtered after the system change and were never replaced (DLG 2005). Reforestation rates were low in Ukraine, partly due to the high human pressure in mountain areas, but mostly because active forest planting essentially stopped after the system change (Buksha et al. 2003).

Overall, only a small proportion (~12%) of the abandoned farmland had been converted to forests by 2000. This offers much potential for additional rapid carbon sequestration, especially since Carpathian forests are highly productive and sequestration rates are highest in young forests (MASR 2003; Grau et al. 2004). Reforestation potential is especially high in Ukraine, where forest cover is substantially lower than in Poland and Slovakia (Kuemmerle et al. 2006), but funds for afforesting abandoned farmland are limited (Nijnik and Van Kooten 2000; Buksha et al. 2003). While conversions from farmland to forests may be beneficial for carbon sequestration and soil protection (Rudel et al. 2005), they are of little value for biodiversity conservation in the Carpathians. Area-sensitive top carnivores and herbivores may benefit from increased forest cover and decreasing human pressure in rural areas. In some areas in Eastern Europe, these circumstances have led to increasing populations (L. Baskin, pers. comm.). However, much of the Carpathian's unique biodiversity is dependent on semi-natural grasslands at intermediate and high elevations (Baur et al. 2006). In these regions, we found highest abandonment rates in Poland and Slovakia. If these lands revert back to forests, much of the biodiversity found in cultural landscapes in the Carpathians would be lost (Cremene et al. 2005).

6 Conclusions

We found extensive farmland abandonment in the border region of Poland, Slovakia, and Ukraine between 1986/88 and 2000. In total, 16.1% of the farmland used before 1990 was no longer used in 2000. Our results suggest that the political and economic changes following the breakdown of the Soviet Union had profound impacts on the profitability of farming in the region. As elsewhere in the world, farmland abandonment was also connected to physiographic factors affecting farmland marginality, for example elevation and slope. However, we also found strong differences in the rates and spatial pattern of farmland abandonment among the three countries in our study area. We suggest that these differences are related to differences in socialist land ownership patterns, post-socialist land reform strategies, and rural population density. In Poland, abandonment rates were twice as high on collectivized land compared to areas that were always privately farmed, emphasizing the importance of land use legacies for land use change. Farmland abandonment in the Carpathians threatens cultural landscapes and their biodiversity, but offers opportunities for increased carbon sequestration, especially in Ukraine where forest cover is low and most abandoned farmland has not yet been afforested. Considering broad-scale political, economic, and societal conditions was essential to understand farmland abandonment in our study area and we suggest that these factors may be equally important land use determinants in marginal regions in other parts of the world.

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Chapter V:
Using image texture to map farmland field size in Eastern Europe

Submitted manuscript

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Abstract

Land cover modifications include changes in land use patterns. Eastern Europe provides unique opportunities to study such changes, because much farmland became parcelized in the post-socialist period (i.e. large fields were broken up into smaller ones). Classification-based remote sensing approaches, however, do not capture these changes and new approaches based on continuous indicators are needed. Our goal was to use image texture to map farmland field size in the border region of Poland, Slovakia, and Ukraine. We fitted linear regression models to relate field size to image texture from Landsat TM/ETM+ images. Texture measures explained up to 93% of the variability in field size. Our field size map showed marked differences among countries. These differences appear to be related to socialist land ownership patterns and post-socialist land reform strategies. Image texture has great potential for mapping land use patterns and may contribute to a better understanding of land cover modifications in Eastern Europe and elsewhere.

1 Introduction

Land use change is one of the primary drivers of environmental change in the earth system (Steffen et al. 2004; Foley et al. 2005). An improved understanding of how land use decisions are made is urgently needed to better assess the consequences of land use change for ecosystem services and human-wellbeing (Rindfuss et al. 2004; GLP 2005). Institutions, laws, and political and socio-economic conditions form the background for land use decisions and may increasingly outrank other factors as determinants of land use (Kaimowitz et al. 1999; Geist and Lambin 2002; Lambin and Geist 2006). Linking land use change with its political and socio-economic boundary conditions however, remains a challenge (Rindfuss et al. 2004; GLP 2005), partly because it may manifest itself in both conversions (changes from one thematic class to another) and modifications (subtle changes within a thematic class) of land cover (Lambin and Geist 2006). However, to date, most studies assessing broad-scale factors of land use change focus on land cover conversions such as deforestation (e.g. Mertens et al. 2000) or urbanization (e.g. Seto and Kaufmann 2003). This is problematic because land cover modifications are widespread and possibly more important than land cover conversions (Lambin et al. 2001). For example, the area affected by forest degradation in the Amazon (e.g. through selective logging) equals at least the area affected by forest conversions (Asner et al. 2005). Agricultural intensification increased the world's food production substantially (Matson et al. 1997), but decreased farmland biodiversity (Donald et al. 2002). Despite their importance, land cover modifications have so far been relatively neglected (Lambin and Geist 2006) and there is a need to quantify their extent, and to assess their relationship to broad-scale political, institutional, and socio-economic conditions.

One prominent case of land cover modifications occurs when the size or configuration of land management units within a land cover class is altered. Such dynamics in land use patterns often take place when changes in politics or socio-economics trigger changes in land use practices, land-management policies, or land-ownership structures (GLP 2005; McConnell and Keys 2005). Central and Eastern Europe's farmland provides a good example of such a process (Swinnen and Mathijs 1997; Lerman et al. 2004). After World War II, socialist governments across Eastern Europe intensified agriculture and shifted ownership from private citizens to the state (i.e. collectivization, Lerman 2001; van Dijk 2003). This transformation was accompanied by widespread spatial reorganization of land management units. Small pre-socialist farms were dissolved and large, state-controlled agricultural enterprises managed almost all farmland (Lerman 2001).

Patterns of farmland changed again drastically after the breakdown of the Soviet Union in 1990, when most Eastern European countries privatized and individualized land management (Lerman 2001), leading to widespread land ownership transfers and the downsizing of farms (Lerman et al. 2004). Land use patterns changed in many areas, as socialist farmland fields were subdivided (Sabates-Wheeler 2002; van Dijk 2003). This physical fragmentation of farmland (hereafter called parcelization) has many economic and ecological consequences. For example, parcelization decreases agricultural efficiency (Sabates-Wheeler 2002) and may lead to abandonment of commonly used infrastructure (Penov 2004). However, parcelization increases farmland biodiversity (Benton et al. 2003), and soil stability (Van Rompaey et al. 2003). Despite the significance of parcelization for rural Eastern Europe, surprisingly little is known about Eastern Europe's land use patterns and how they changed since 1990.

This lack of information is unfortunate because studying land use patterns offers unique opportunities to better understand the effects of changing institutions, politics, and socio-economics on land use decisions. Moreover, field size can be interpreted as an indicator of land ownership and land management, particularly when comparing land use patterns among different countries with similar environmental conditions. However, mapping field size in Eastern Europe is challenging, because cadastral data are largely unavailable or of unknown accuracy. Remote sensing is an alternative that can overcome some of these problems.

Very few studies used remote sensing for automated assessments of field size. This is not surprising, because most conventional image classification and change detection methods stratify images into discrete classes (Southworth et al. 2004; Lambin and Geist 2006). Using classification based methods to map field size requires classifying all occurring crop types. Such detailed classifications are only possible for detailed time series of satellite images or where crops have unique spectral properties, for example in the case of rapeseed (Elliott et al. 2004). In most cases, however, acquiring training data for detailed crop type classifications is not feasible, and the spectral similarity of crops inhibits detailed classifications. Field boundaries can also be delineated using image segmentation (Evans et al. 2002; Lloyd et al. 2004). Yet, this is only possible where fields are much larger than the dimensions of a pixel, because mixed pixels result in poor boundary discrimination (Turner and Congalton 1998; Silleos et al. 2002; Ozdogan and Woodcock 2006). Small fields are common in Eastern Europe due to farmland parcelization (Sabates-Wheeler 2002; van Dijk 2003) and this inhibits the use of image segmentation to delineate field boundaries.

An alternative is to characterize land cover using continuous variables, which can detect subtle changes (Southworth et al. 2004; Turner 2005). A few such methods exist (e.g. change vector analysis, spectral mixture analysis, Coppin et al. 2004), but are based on spectrally homogeneous land cover types (i.e. changes in the signal are related to changes in land cover condition). This is problematic in the case of farmland, where different crops and phenology result in high spectral variability. Moreover, many methods focus on the spectral domain only (Coppin et al. 2004; Southworth et al. 2004), but the spatial domain also contains important information (Chica-Olmo and Abarca-Hernandez 2000; Cihlar 2000). Methods based on continuous data that integrate the spatial domain (Southworth et al. 2004; Turner 2005) and allow for mapping structural modifications of land cover, such as farmland parcelization, are therefore needed.

Image texture measures tonal variations in the spatial domain by quantifying the variability and spatial distribution of grey level values (Baraldi and Parmiggiani 1995; Chica-Olmo and Abarca-Hernandez 2000). Because structural information can be important to discriminate between land cover categories, texture measures have widely been used in land cover classifications (Berberoglu et al. 2000; Presutti et al. 2001). For example, texture measures improve classification of forests (Franklin et al. 2000; Coburn and Roberts 2004), urban areas (Dekker 2003), and agricultural crops (Anys and He 1995; Lloyd et al. 2004). Texture measures have much less frequently been used to derive continuous, quantitative variables, and existing studies have mostly assessed vegetation structure in natural ecosystems (Wulder et al. 1998; Asner et al. 2002; Asner et al. 2003). However, to our knowledge no study used texture to map field sizes. This is unfortunate because small fields likely result in high local heterogeneity due to the variability in crop types and phenology, whereas large fields are locally homogeneous. Measures of spatial autocorrelation are sensitive to these field-size-dependent textural characteristics (Lloyd et al. 2004; Ozdogan and Woodcock 2006). Image texture therefore, should be able to quantify differences in land use patterns and provide an indicator of field size.

Only two prior studies used remote sensing to address field size in Eastern Europe. Visual interpretation of a 1998 Landsat Thematic Mapper (TM) image provided mean field size for six types of villages in southeast Poland and showed that traditional villages had much smaller fields compared to villages with more intensive land use (Angelstam et al. 2003). Similar visual interpretation in Albania revealed widespread parcelization between 1988 and 2003 (Müller and Munroe 2007). Thus, existing studies were confined to small study areas within single countries. No study mapped field size from remote sensing images for larger areas in Eastern Europe or has compared land use patterns among countries.

Our goal was to map field sizes in 2000 in a study area in Eastern Europe (the border triangle of Poland, Slovakia, and Ukraine) using image texture. Our specific objectives were:

(1) to build a statistical model that relates field size and image texture

(2) to apply this model to our study area to map field size

(3) to compare land use patterns among countries in our study area

2 Study area

We studied field sizes in the border triangle of Poland, Slovakia, and Ukraine (Figure V-1). The boundaries of the study area were based on the extent of one Landsat TM scene (path/row 186/26), landscape features such as rivers and valleys, and administrative boundaries. The 17,800km^2 study area is characterized by a moderately cool and humid climate (average annual temperature of 5.9°C, mean precipitation of 1,100-1,200mm, Augustyn 2004). Bedrock is largely dominated by Carpathian flysh (sandstone and shale) (Denisiuk and Stoyko 2000), but some andesite-basalts occur in the southwest of the study area (Herenchuk 1968). Dominating soils are cambisols together with podzols in the mountains, whereas podzoluvisols, greysems, gleysols, and fluvisols dominate the plains. The region has mountainous topography (200 - 1,480m altitude). The three main altitudinal zones of potential natural vegetation are: the foothill zone (< 600m) dominated by broadleaved forest, mostly beech (*Fagus sylvatica*) and oak (*Quercus robur, Quercus petraea*); the montane zone (600-1,100m) characterized by beech, mixed with silver fir (*Abies alba*) and sycamore (*Acer pseudoplatanus*); and alpine meadows with dwarfed beech above the timberline (1,100-1,200m, Denisiuk and Stoyko 2000).

Land use has substantially altered the study area, particularly in the 19th and 20th century. Population growth and agricultural intensification resulted in increasing agricultural area, mainly at the expanse of forests (Turnock 2002; Augustyn 2004). Today, the densely settled plains and the foothills of the study area are largely farmed (Kuemmerle et al. 2006).

Forests dominate the montane zone (>60%, Kuemmerle *et al.* 2006), but farmland and pastures are widespread in mountain valleys, particularly in Slovakia and Ukraine, where population density is much higher than in Poland (Augustyn 2004). Growing season length varies with altitude (from more than 270 days below 500m to less than 220 days above 800m) (Zarzycki and Glowacinski 1970). Dairy farming and cattle breeding are important agricultural activities. Cereal (e.g. winter wheat, buckwheat), oil crops (e.g. rape, sunflowers), flax, corn, and potatoes are cultivated in the plains. Agriculture is an important source of income, but most of the agricultural goods are produced for local markets. Moreover, many land owners depend on subsistence farming, particularly in Ukraine.

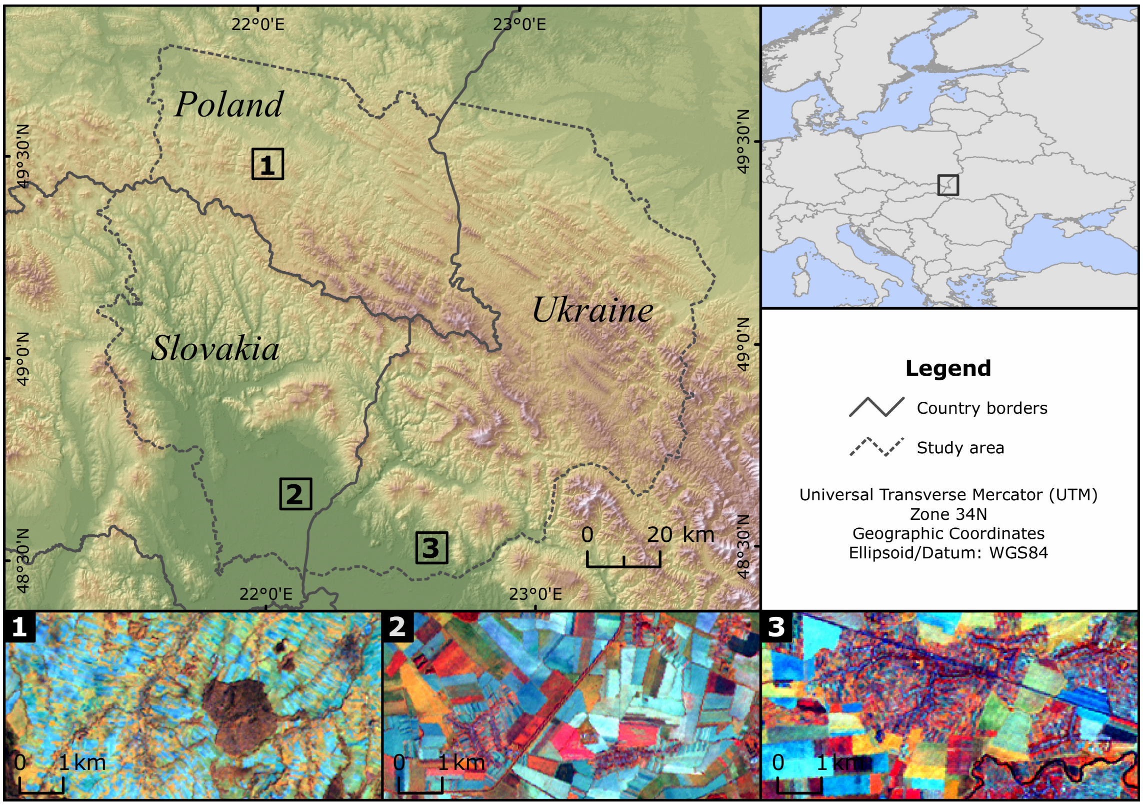

Figure V-1: Top: Study area in the border region of Poland, Slovakia, and Ukraine in the Carpathians. Bottom: Example of land use pattern in the three countries Poland, Slovakia, and Ukraine (Landsat Enhanced Thematic Mapper Plus image from 30th September 2000; band combination: red = band 4, green = band 5, blue = band 3).

Almost all farmland in Slovakia and Ukraine was collectivized during socialism and managed in large, state-controlled agricultural enterprises. In Slovakia, cooperatives prevailed, and land owners retained property rights to their fields. In contrast, in Ukraine all land was owned by the state (Lerman 1999; Csaki et al. 2003), but in Poland, most farmland was never collectivized (Lerman et al. 2004). A special case were some parts of the Polish region of the study area that were forcefully depopulated following border changes between the Soviet Union and Poland in 1947, and these lands were transferred into state ownership (Turnock 2002; Augustyn 2004). After 1990, Slovakia, Poland, and Ukraine launched land reforms to privatize farmland and to individualize land use; yet, the countries chose diverse land reform strategies (Lerman *et al.* 2004). As a result, the region has heterogeneous land use patterns and is particularly well suited to study how changes in land ownership and land management manifest themselves in land use pattern, and to explore the relationship of field size and image texture.

3 Data and Methods

3.1 Datasets used

We acquired one Landsat TM (8/21/2000) and two Landsat Enhanced Thematic Mapper Plus (ETM+) images (6/6/2000 and 9/30/2000) from path/row 186/26 to map post-socialist field size patterns in our study area. Precise co-registering of is necessary for accurate analysis of multitemporal images (Coppin et al. 2004). We orthorectified the images and registered them to the Universal Transverse Mercator coordinate system (World Geodetic System 1984 datum and ellipsoid) (Hill and Mehl 2003a; Kuemmerle et al. 2006). Radiometric correction based on radiometric transfer models was carried out to minimize the effect of differing atmospheric and illumination conditions among images (Hill and Mehl 2003a; Kuemmerle et al. 2006). Thermal bands were not retained due to their lower spatial resolution. Three Ikonos images and twelve Quickbird images available via Google Earth (http://earth.google.com) were used to digitize farm fields as training samples (see section 3.2). All images had been acquired between 2002 and 2006, and together covered an area of 2,890km² (16% of the study area). The Ikonos images were georectified by us while the Quickbird images were already orthorectified. All images were pan-sharpened, with a spatial resolution of 1m for the Ikonos data and 0.67m for the Quickbird images.

3.2 Sample of fields

To derive ground truth data, we digitized farm fields from IKONOS and Quickbird images for 35 independent sample plots, where each sample plot consisted of many fields. Sample locations were determined at random, maintaining a minimum distance of 1km between sample plots to reduce potential effects of spatial autocorrelation. This distance was chosen based on the range of positive spatial autocorrelation in semi-variograms of selected texture measures (see section 3.3). Variograms were based on 1,000 random locations, directional variograms were used to account for potential directionality, and Gaussian variogram models were fitted to estimate the range.

Field size differed greatly in the study area (<0.1ha to >100ha) and deciding upon the size of the sample plots carefully was therefore important. We defined a sample plot as a fixed number of fields, rather than a fixed area because no single sample plot size would have been well suited to all conditions. To determine the necessary number of fields, we evaluated how mean field size changed as a function of the number of fields. We did so for two circular test areas, one with very small fields (Poland, 151ha, n=331 fields), and one with large fields (Slovakia 1,787ha, n=173 fields). The locations of these test areas were determined based on field visits and expert knowledge. Fields were consecutively added to the calculation of the mean, based on their centroid's distance to the center point of the test area. The curves of both test areas suggested that mean field size became stationary after approximately 30 fields were included (data not shown). We therefore digitized the 30 fields from the IKONOS and Quickbird images that were closest to the center of each of our 35 sample plots. We used less than 30 fields if sample plot size exceeded 200ha (including the field necessary to reach this limit). The area covered by a single sample plot ranged from 9 – 262ha. Non-farmland was not digitized and we digitized a total of 770 fields.

3.3 Texture measures

Texture measures quantify heterogeneity in the spatial distribution of grey values within a local neighborhood, either based on the 1st-order (occurrence) or 2nd-order (co-occurrence) grey level histogram (Haralick et al. 1973; Anys and He 1995). Different texture measures capture different aspects of spatial variability. Their values also partly depend on the size of the moving window used to calculate them (Anys and He 1995; Berberoglu and Curran 2004). We selected 13 texture measures that are relevant to describe land cover features (Anys and He 1995; Berberoglu and Curran 2004), including many with low collinearity (Baraldi and Parmiggiani 1995; St-Louis et al. 2006). The set of texture measures that we chose included five occurrence measures (range, mean, variance, entropy, and skewness), and eight co-occurrence measures (2nd mean, sum of squares variance, homogeneity, contrast, dissimilarity, 2nd entropy, angular second moment, and correlation) (Haralick et al. 1973; Anys and He 1995). The grey-level co-occurrence matrix was calculated unidirectionally (135 degrees), because field visits and directional variograms did not suggest any particular textural orientation of farmland crops in our study area.

Texture measures were calculated for each of the six multispectral TM/ETM+ bands. We calculated texture measures for the June, August, and September images to test for phenology effects. We calculated the thirteen texture measures for seven window sizes (3, 5, 7, 9, 15, 21, and 51 pixels). In total, we calculated 1,638 texture measures (18 bands [3 images] * 13 texture measures * 7 window sizes). To relate field size to texture measures at the sample plot level we summarized texture by calculating mean and standard deviation of all pixels within a sample plot for each texture measure. The mean denotes the average texture for each sample plot, whereas the standard deviation texture is a measure of variability of texture per sample plot. All texture measures were calculated using ENVI/IDL image processing software (RSI 2003).

3.4 Statistical analysis

We fitted regression models to explore the relationship between field size and image texture. As the dependent variable, we used mean field size per sample plot. Histograms and normal quantile-quantile (QQ)-plots suggested a lognormal distribution, and we transformed field size to a normal distribution using the common logarithm. We used sample plot level mean and standard deviation texture as independent variables. Univariate and multiple regression models were fitted to determine texture measures that were good predictors of field size. To fit models and to select the best models, we used a best-subsets method based on the leaps procedure and an exhaustive search method (Miller 1990; R Development Core Team 2006). The best-subsets regression searches all possible combinations of *n* independent variables, where *n* is the number of covariates in a model, and ranks models according to their goodness-of-fit. Correlation matrices indicated strong collinearity between some input variables. To avoid over-fitting, we limited the maximum number of covariates in a model (*n*) to three (i.e. allowing for one-, two-, and three-dimensional models). Regression models were fitted for two groups of variables: models that used mean texture only (group I models), and models that incorporated mean and standard deviation texture (group II). Best models were derived for different selections of input variables. First, we selected best subsets for each window size and image, using 78 variables (6 bands * 13 texture measures) for group I models, and 156 variables (78 * 2) for group II models. Second, we selected the best subsets per window size when using input variables from all three images (78 * 3 = 234 for group I, 156 * 3 = 468 for group II) to assess whether combinations of texture derived from phenologically different dates improved predictions. Finally, we fitted models for each image based on the texture measures for all window sizes (78 * 7 = 546 for group I models, 156 * 7 = 1092 for group II models) to investigate whether combinations of texture measures from different window sizes improved predictions.

We derived the best one-, two-, and three-dimensional model for each of the groups of variables described above. Some of our input variables were collinear and we therefore expected several combinations of texture measures to predict field size equally well. Collinearity among input variables is not disadvantageous when using the best subsets routine, because all possible models with *n* covariates are compared. Models based on covariates with low collinearity likely explain more of the total variance than models with collinear covariates. To compare among models, we calculated two measures of goodness-of-fit: the adjusted coefficient of determination (R^2), and the Bayesian Information Criterion (BIC, Schwarz 1978). Both measures account for the number of covariates in a model, thus allowing comparison of models of different dimensionality. Given any two estimated models, the model with the lower BIC and the higher adjusted R^2 was preferred. We assumed models performed equally well if their adjusted R^2 values differed by less than 0.02 (equaling a BIC difference of ~3). We also calculated the *p*-value and the Bonferonni corrected *p*-value for all coefficients to evaluate their significance. The Bonferonni correction considers the number of input variables. Coefficients remain significant if their *p*-value is smaller than 0.05/n, where n denotes the number of input variables. To test the robustness of our models, we calculated cross-validation prediction errors using a leave-one-out procedure and a five-fold cross-validation for the best univariate and multiple regression models (Burman 1989). We also controlled for the presence of spatial autocorrelation in the residuals in our best multiple regression models based on variograms and found no spatial autocorrelation. All statistical analyses were carried out using R 2.4.1 (R Development Core Team 2006).

3.5 Applying the model to images

Once the best mean texture models (group I) were selected, we applied them to the entire study area to derive a map of field size. Models that used standard deviation texture (group II) performed better. However, we could not apply these models to full images, because the different sizes of the sample plots inhibited the spatially explicit estimation of standard deviation texture. All forests, water bodies, and settlements were masked out using previous land cover classifications (Kuemmerle et al. 2006; Kuemmerle et al. 2007a). We excluded all areas above 1,000m elevation because farmland does not occur above this altitude in the Carpathians. Clouds in the September 2000 image (0.02% of the study area) were masked out. The best mean texture models (group I) were applied to all unmasked pixels to derive a map of field size for the year 2000. Our pixel-based models do therefore not allow for mapping the size or boundaries of single fields but rather estimate mean field size for the surroundings of a given pixel. Because field size was log-transformed, outliers resulted in unrealistically small or large field sizes. To account for this, we used a 5%-cutoff at the extreme ends of the field size distribution.

4 Results

4.1 Statistical models

Texture measures explained the majority (i.e. up to 93%) of the variability in field size. Generally, models based on mean and standard deviation texture (group II models) explained more variability in field size than models based on mean texture only (group I models) (Table V-1 and Table V-2). Multiple regression models using two or three independent variables predicted field size substantially better than univariate models. The increase in adjusted R^2 was strongest from one to two dimensional models with an average of 0.17 (range: 0.09-0.29) for models that used mean texture (group I models, Table V-1), and 0.12 (range: 0.04-0.24) for models using mean and standard deviation texture (group II models, Table V-2). Adjusted R^2 values improved less when adding a third covariate (on average 0.07 for both, group I and group II models). All coefficients in the univariate models were highly significant ($p<0.0001$) and remained significant after Bonferonni correction. The significance of some coefficients decreased in the two- and three-dimensional models, but all coefficients were significant at $p<0.05$ and most coefficients were significant using the Bonferonni-corrected p-value (Table V-1 and Table V-2).

Some texture measures predicted field size better than others. First-order entropy was the best single predictor of field size (Figure V-2), and most of the best univariate models were based on either 1st or 2nd-order entropy, or angular second moment. The measures used in the best univariate models were highly collinear (for example, a correlation coefficient of 0.99 between 1st and 2nd-order entropy). In the multiple regression models, these measures were complemented by 1st and 2nd-order mean, variance, and correlation (Table V-3). Some texture measures were rarely included in the two- and three-dimensional models (e.g. homogeneity, contrast, and dissimilarity). Texture measures included in one of the best

Table V-1: Regression models for different combinations of texture measures and window sizes for models that included mean texture (group I models). Best models for each subgroup (one-, two-, or three-dimensional) are in bold. Acronyms: #V = number of input variables, WS = window size, adjR^2 = adjusted R^2, BIC = Bayesian Information Criterion, #BM = number of equally good best models (i.e. difference in adj. R^2 < 0.02 to the absolute best model); Significance: p<0.0001=***, <0.001=**, <0.01=*, <0.05=a; b indicates cases were all coefficients remained significant after Bonferonni correction.

	#V	WS	one-dimensional models				two-dimensional models				three-dimensional models			
			adjR^2	BIC	p-value	#BM	adjR^2	BIC	p-values	#BM	adjR^2	BIC	p-values	#BM
June 2000	78	3	**0.59**	**-25.15**	****** b***	1	0.74	-38.17	**/*** b	2	0.76	-38.53	**/*/***	33
	78	5	0.58	-24.58	*** b	1	0.69	-32.13	*/***	11	0.75	-38.22	***/***/** b	19
	78	7	0.56	-22.91	*** b	2	0.68	-31.63	**/***	8	0.77	-40.24	***/***/** b	9
	78	9	0.55	-22.26	*** b	1	0.69	-32.43	***/*** b	6	0.77	-40.28	***/***/** b	14
	78	15	0.49	-17.73	*** b	1	0.69	-32.89	***/*** b	2	0.76	-39.11	***/*/*** b	18
	78	21	0.46	-15.73	*** b	2	0.68	-31.17	***/*** b	2	0.73	-34.63	***/a/***	41
	78	51	0.45	-14.71	*** b	1	0.57	-21.28	***/*** b	1	0.67	-27.72	**/***/*** b	8
	546	all	0.59	-25.15	*** b	2	0.74	-38.17	**/***	4	0.78	-41.96	**/***/***	>200
August 2000	78	3	0.55	-21.56	*** b	1	0.64	-27.04	***/*** b	11	0.74	-35.55	**/***/*** b	4
	78	5	0.55	-21.57	*** b	2	0.65	-27.86	***/*** b	9	0.69	-29.68	*/***/*	25
	78	7	0.53	-20.34	*** b	3	0.65	-27.95	***/*** b	13	0.69	-30.04	a/*/a	85
	78	9	0.51	-18.97	*** b	3	0.67	-30.37	***/*** b	6	0.74	-35.82	*/***/***	6
	78	15	0.46	-15.37	*** b	1	0.66	-29.04	***/*** b	13	0.69	-30.14	*/*/***	69
	78	21	0.41	-12.49	*** b	2	0.64	-27.54	***/*** b	12	0.68	-28.50	a/***/***	76
	78	51	0.39	-11.39	*** b	1	0.60	-23.23	***/*** b	4	0.66	-26.38	*/a/***	35
	546	all	0.55	-21.57	*** b	5	0.73	-37.69	***/*** b	24	0.79	-43.52	***/**/**	93
September 2000	78	3	0.52	-19.38	*** b	1	0.67	-30.25	***/*** b	9	0.71	-32.06	*/***/***	21
	78	5	0.52	-19.62	*** b	2	0.68	-31.49	***/*** b	10	0.73	-35.06	*/a/*	14
	78	7	0.52	-19.49	*** b	2	0.70	-33.21	***/*** b	8	**0.84**	**-52.27**	*****/***/*** b**	6
	78	9	0.51	-18.62	*** b	2	0.72	-36.13	***/*** b	6	0.82	-49.00	***/***/*** b	4
	78	15	0.48	-16.72	*** b	4	**0.74**	**-38.64**	*****/*** b**	4	0.80	-45.19	***/***/** b	6
	78	21	0.46	-15.65	*** b	3	0.67	-29.98	***/*** b	8	0.73	-34.69	***/***/*	12
	78	51	0.43	-13.88	*** b	2	0.57	-20.82	***/*** b	12	0.63	-24.22	***/**/*** b	10
	546	all	0.52	-19.62	*** b	7	0.74	-38.64	***/*** b	35	0.85	-54.92	***/***/***	43
all three images	234	3	0.59	-25.15	*** b	1	0.74	-38.17	**/*** b	2	0.78	-42.76	**/***/*	18
	234	5	0.58	-24.58	*** b	1	0.69	-32.13	*/***	37	0.77	-40.11	***/***/*** b	35
	234	7	0.56	-22.91	*** b	2	0.70	-33.21	***/*** b	22	0.84	-52.27	***/***/*** b	6
	234	9	0.55	-22.26	*** b	1	0.72	-36.13	***/*** b	8	0.82	-49.00	***/***/*** b	4
	234	15	0.49	-17.73	*** b	3	0.75	-40.61	***/*** b	9	0.81	-46.60	*/***/***	23
	234	21	0.48	-15.73	*** b	5	0.77	-40.53	***/*** b	14	0.83	-46.83	*/***/***	51
	234	51	0.45	-14.71	*** b	2	0.71	-34.45	***/*** b	6	0.79	-43.81	***/**/***	14

multiple regression models all displayed a low degree of collinearity (for example, correlation coefficients of <0.10 between mean and entropy).

Goodness-of-fit varied strongly among Landsat bands used to derive the texture measures, but model predictions were similar for collinear Landsat TM/ETM+ bands (e.g. bands in the visual domain). Most texture measures included in our best models were based on short wavelength infrared (SWIR) and visible bands (Table V-3). The SWIR bands were particularly important for the univariate mean texture models (group I); whereas texture measures based on the visible bands were mostly included in the univariate group II and in

Table V-2: Regression models for different combinations of texture measures and window sizes for models that included mean and standard deviation texture (group II models). Best models for each subgroup (one-, two-, or three-dimensional) in bold. Acronyms: #V = number of input variables, WS = window size, adjR² = adjusted R², BIC = Bayesian Information Criterion, #BM = number of equally good best models (i.e. difference in adj. R² < 0.02 to the absolute best model); Significance: p<0.0001=***, <0.001=**, <0.01=*, <0.05=a; b indicates cases were all coefficients remained significant after Bonferonni correction.

	#V	WS	one-dimensional models				two-dimensional models				three-dimensional models			
			adjR²	BIC	p-value	#BM	adjR²	BIC	p-values	#BM	adjR²	BIC	p-values	#BM
June 2000	156	3	0.59	-25.15	*** b	2	0.81	-49.28	***/*** b	6	0.83	-50.87	***/a/***	78
	156	5	0.74	-41.11	*** b	1	0.79	-45.39	***/**	24	0.84	-53.40	**/***/**	54
	156	7	0.78	-46.19	*** b	3	**0.83**	**-54.03**	***/***	14	0.86	-58.99	**/***/** b	63
	156	9	**0.78**	**-46.97**	***** b**	1	0.83	-53.77	*/***	15	0.85	-56.38	***/*/*	115
	156	15	0.72	-38.80	*** b	1	0.80	-47.02	*/***	4	0.83	-51.49	**/***/***	10
	156	21	0.68	-33.31	*** b	1	0.76	-42.00	**/***	6	0.82	-49.48	***/***/**	19
	156	51	0.68	-33.31	*** b	1	0.74	-38.21	***/**	18	0.80	-46.15	***/***/*** b	19
	1092	all	0.78	-46.97	***	3	0.84	-54.67	***/**	95	0.89	-65.63	***/***/***	127
August 2000	156	3	0.59	-24.94	*** b	1	0.71	-34.65	***/*** b	2	0.75	-37.76	***/***/** b	19
	156	5	0.67	-32.90	*** b	1	0.71	-34.30	a/**	21	0.78	-42.20	***/***/*** b	12
	156	7	0.67	-32.54	*** b	1	0.73	-36.66	***/*** b	14	0.79	-43.16	***/***/*** b	40
	156	9	0.63	-28.79	*** b	1	0.74	-38.63	***/*** b	10	0.80	-44.65	***/***/*** b	55
	156	15	0.54	-20.78	*** b	2	0.74	-38.74	***/*** b	10	0.84	-52.68	***/***/*** b	6
	156	21	0.50	-18.05	*** b	3	0.74	-39.15	***/*** b	8	0.83	-50.32	***/***/**	20
	156	51	0.50	-18.05	*** b	3	0.70	-33.34	***/*** b	4	0.82	-50.00	***/***/*** b	12
	1092	all	0.67	-32.90	*** b	2	0.76	-42.09	***/*** b	105	0.86	-58.94	***/***/*** b	36
September 2000	156	3	0.55	-21.79	*** b	1	0.67	-30.25	***/*** b	13	0.75	-36.99	**/***/**	34
	156	5	0.57	-23.2	*** b	1	0.68	-31.5	***/*** b	15	0.77	-40.06	**/***/** b	11
	156	7	0.59	-24.92	*** b	1	0.70	-33.21	***/*** b	15	0.84	-52.27	***/***/*** b	6
	156	9	0.60	-25.95	*** b	2	0.72	-36.13	***/*** b	8	0.82	-49.00	***/***/*** b	4
	156	15	0.58	-24.13	*** b	5	0.76	-40.73	***/*** b	10	0.82	-49.95	***/***/**	39
	156	21	0.55	-22.13	*** b	1	0.75	-40.32	***/*** b	3	0.80	-45.99	***/***/*	28
	156	51	0.55	-22.13	*** b	1	0.72	-36.18	***/*** b	4	0.82	-49.95	***/***/** b	10
	1092	all	0.6	-25.95	*** b	3	0.77	-43.39	***/*** b	66	0.85	-56.16	***/**/*** b	155
all three images	468	3	0.59	-25.15	*** b	3	0.81	-49.28	***/*** b	6	0.85	-54.68	***/***/*** b	31
	468	5	0.74	-41.11	*** b	1	0.80	-48.14	***/*	22	0.87	-61.49	***/***/*	97
	468	7	0.78	-46.19	*** b	3	0.84	-54.71	***/**	36	0.92	-77.31	***/***/**	64
	468	9	0.78	-46.97	*** b	1	0.85	-58.35	**/***	17	**0.93**	**-84.13**	*****/***/*** b**	39
	468	15	0.72	-38.80	*** b	1	0.82	-51.31	***/*** b	19	0.91	-75.25	***/***/*** b	74
	468	21	0.68	-33.31	*** b	1	0.81	-49.85	***/*** b	10	0.90	-70.15	***/***/*** b	83
	468	51	0.68	-33.31	*** b	1	0.79	-45.47	***/*** b	7	0.90	-68.33	***/***/*** b	19

the two- and three-dimensional models. As expected due to the collinearity among different texture measures and Landsat bands, several models performed equally well (i.e. difference of adjusted R² <0.02). The number of similar models was generally lower for group I models compared to group II models and increased with the number of covariates allowed (Table V-1 and Table V-2).

The goodness-of-fit of the regression models varied among window sizes and was best at small window sizes (Table V-1 and Table V-2). Our univariate models revealed that most texture measures had a clear peak in goodness-of-fit at small or intermediate window sizes and R² values decreased rapidly for larger window sizes (Figure V-3). Combining texture measures from different window sizes did not substantially improve model predictions (i.e. increase in adjusted R² <0.02), both for group I models (Table V-1), and for group II models (Table V-2).

Figure V-2: Example of an area characterized by heterogeneous land use pattern in high-resolution Quickbird data (left), June 2000 Landsat ETM+ data (1st principal component, middle), and image texture derived from the Landsat image (1st-order entropy of band 7 calculated at a window size of 3 pixels, right). The subset is centred on the village of Bezovce in Slovakia (21.15E, 48.63N).

Comparing regression models based on texture measures from different images revealed moderate differences in goodness-of-fit. For group I models, texture measures from the June and September images yielded higher model predictions than models based on the August image (Table V-1), but combining texture measures from all three images did not increase goodness-of-fit substantially. This was different for group II models. Goodness-of-fit was comparable among the three dates, however, predictions improved when combining texture from different images (Table V-2). Our best model explained 93% of the variance and used three covariates: mean angular second moment (September 2000 image, TM band 6), standard deviation of 1st-order entropy (June 2000, band 1), and standard deviation variance (August 2000, band 3); all calculated for a window size of 9 pixels.

Table V-3: Example of the number of times each texture measure was included in the series of regression models containing one (n=1), two (n=2 models), or three (n=33) covariates that performed equally well (i.e. diff. in adjusted R² <0.02) for mean texture of June 2000 (window size 3, total number of variables = 78). Acronyms: range (RA), 1st-order mean (M1), variance (VA), 1st-order entropy (E1), skewness (SK), 2nd-order mean (M2), sum of squares variance (SS), homogeneity (HO), contrast (CO), dissimilarity (DI), 2nd-order entropy (E2), angular second moment (SM), correlation (CR), near infrared band (NIR), short wavelength infrared bands (SWIR1, SWIR2).

	RA	M1	VA	E1	SK	M2	SS	HO	CO	DI	E2	SM	CR
Blue		5	1			3	1				4	4	19
Green		8	1			6	1						
Red		4				4							
NIR		1			2	1							
SWIR1												1	
SWIR2				30				1		1			6

Among all the models fitted, we selected the best one-, two-, and three-dimensional model for group I and group II based on the adjusted R² and BIC statistics, and chose only models where all coefficients remained significant after Bonnferoni correction. In cases where several models performed equally well (i.e. difference in adjusted R² <0.02), we selected the model that was derived using a smaller selection of input variables, resulting in six best models. Cross-validation for these six models (bold models in Table V-1 and Table V-2) showed that the robustness of the multiple regression models was relatively high (Table V-4)). Prediction errors of the multiple regression models were substantially lower than those of the univariate models (by a factor of 2-3). Errors ranged from 0.20 to 1.41 (log field size) and were lower for group II compared to group I models. The prediction errors were similar when using a leave-one-out strategy or a five-fold cross-validation approach (Table V-4).

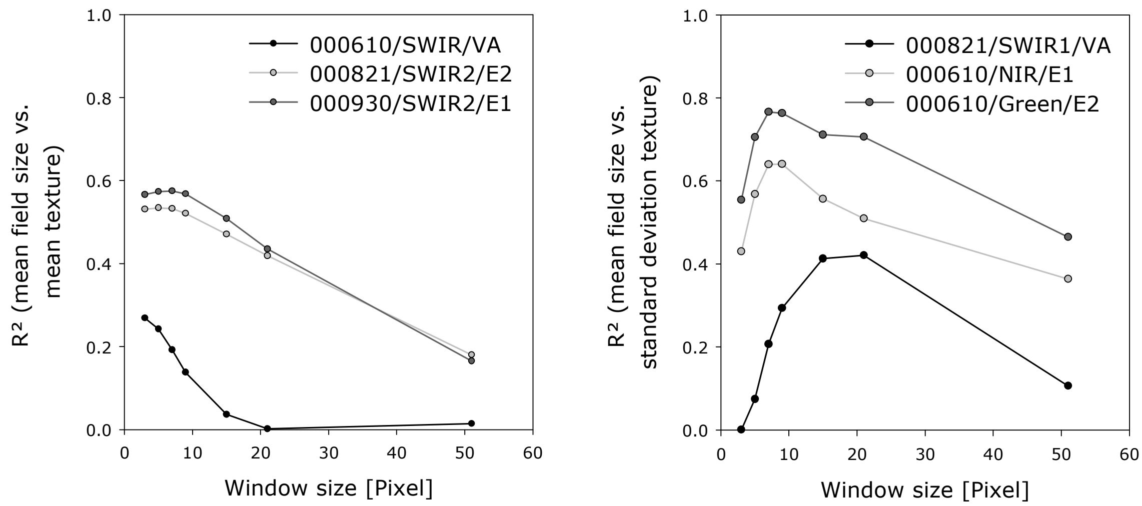

Figure V-3: Examples of the relationship between prediction accuracy (R² of field size vs. texture measures) and window size used to calculate texture measures. Mean field size was estimated using mean texture (left) and standard deviation of texture (right).

Table V-4: Mean prediction errors of mean field size (log) for the one- two-, and three-dimensional group I (mean texture) and group II (mean and standard deviation texture) models. Cross-validation was carried out for the best models per subgroup (bold models in Table 1 and Table 2) using a leave-one-out strategy and a five-fold cross-validation approach.

	one-dimensional model		two-dimensional model		three-dimensional model	
	leave-one-out	five-fold	leave-one-out	five-fold	leave-one-out	five-fold
group I models	1.41	1.40	0.94	0.90	0.59	0.63
group II models	0.80	0.84	0.61	0.58	0.25	0.26

4.2 Applying the model to images

We used the absolute best two- and three-dimensional mean texture models (group I) based on the adjusted R^2 to map field size in our study area. Because our ultimate goal was to predict field size, we did not have to consider other equally good models. The optimal two-dimensional model used two September 2000 texture measures calculated at a window size

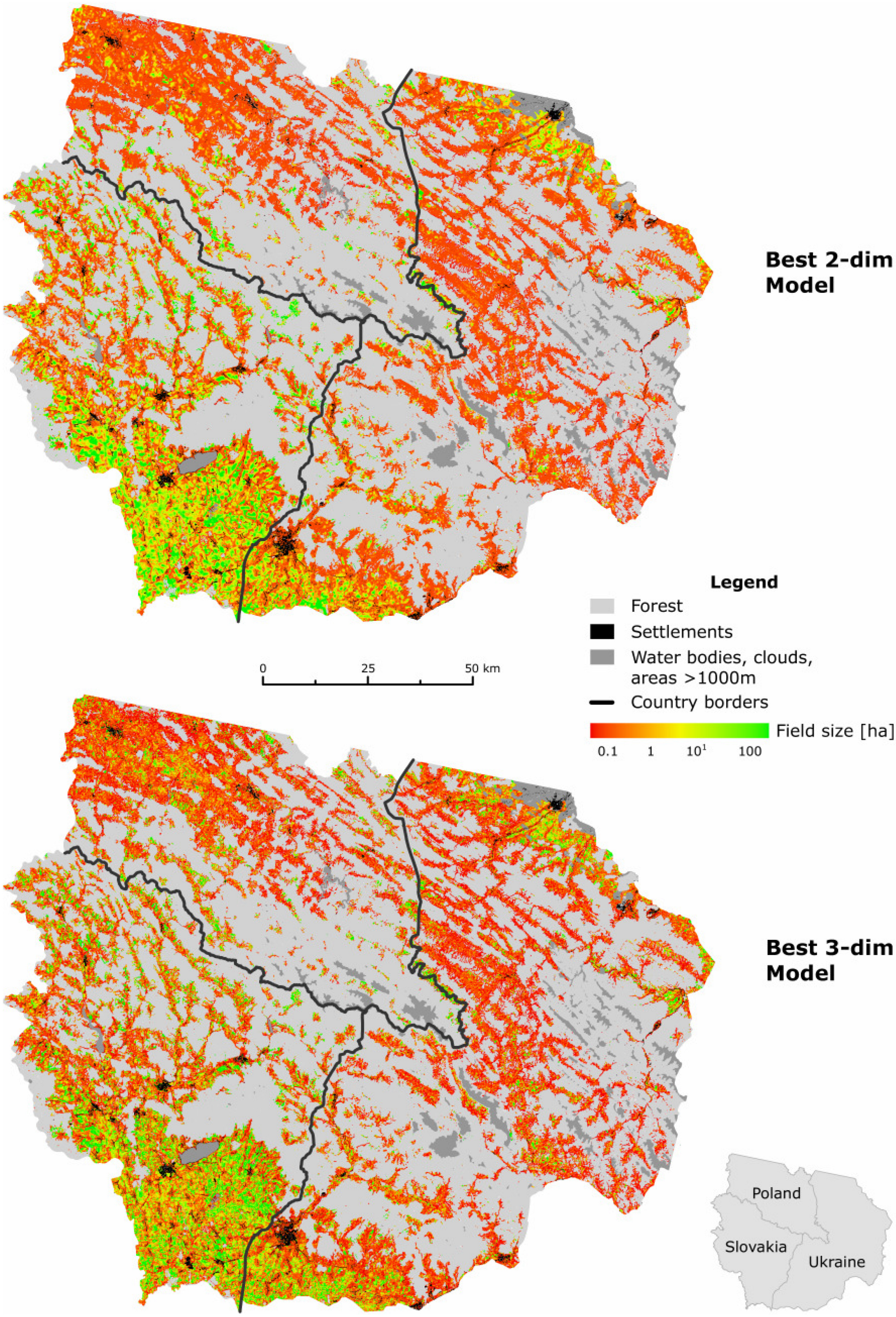

Figure V-4: Field size map of the border region of Poland, Slovakia, and Ukraine for the year 2000. Top: map derived using the best two-dimensional mean texture model; Bottom: map derived using the best three-dimensional mean texture model. The three-dimensional map is shown using the color scheme of the two-dimensional map for better comparison. (Coordinate System: UTM / Zone 34N; Ellipsoid/Datum: WGS84) of 15 pixels (2^{nd}-order mean and correlation from band 3) and explained about 74% of the variance in field size at the sample plot level (Table V-1). The absolute best three-dimensional mean texture model relied on three September 2000 texture measures derived for a window size of 7 pixels (variance of TM band 1, correlation of band 2, and 2^{nd}-order mean of band 3) and had an adjusted R^2 of 0.84 (Table V-1). Applying these best two- and three-dimensional models to all unmasked pixels of the September 2000 image yielded field sizes between 0.07-142ha and 0.04-1,565ha, respectively (10^{th} and 90^{th} percentile of all estimated pixels). The field size map revealed diverse spatial patterns of field size across our study area, and maps from the two-dimensional and three-dimensional models were highly similar (Figure V-4). Large fields dominated the plains in the north and south whereas mountain valleys were dominated by small fields. Field visits and visual comparison with the Quickbird and Ikonos images confirmed these patterns.

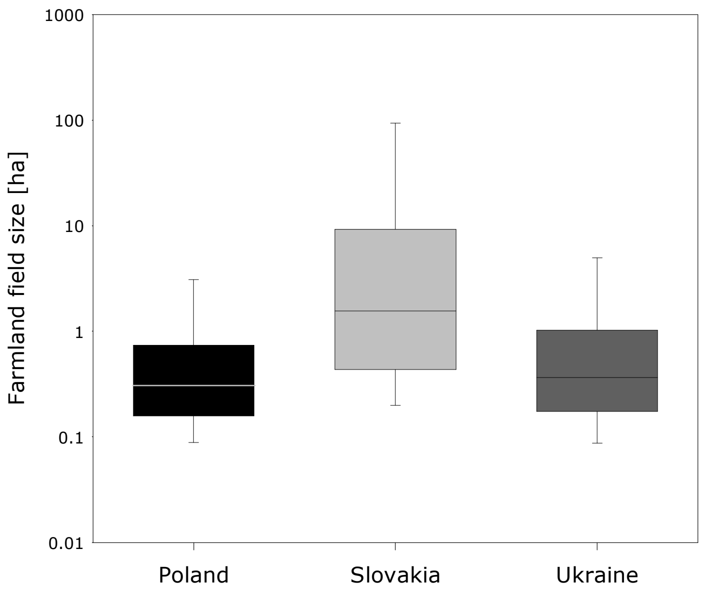

Figure V-5: Distribution of field sizes for the Polish, Slovak, and Ukrainian region of the study area. Whiskers indicate the 90^{th} and 10^{th} percentiles.

Field size patterns in Poland, Slovakia, and Ukraine differed markedly. Poland had small fields in most areas (Figure V-5), but some large fields (>1ha) occurred in the valleys along the Polish-Slovak border and in the northwest of the study area (figure V-4). In Slovakia, field sizes were substantially larger than in the other two countries (Figure V-5). In particular, the southern plains were characterized by very large fields, often exceeding 100ha. Mountain valleys had a mix of large and small fields, with valleys in the North exhibiting a higher percentage of large fields than valleys in the South. Ukraine showed the most heterogeneous patterns of field sizes. Although the overall distribution of field sizes was similar to Poland's distribution (Figure V-5), small and large fields were much more clustered in Ukraine. Mountain valleys were characterized by very small fields (<0.1ha, figure V-4). Large fields were mainly found in the northern and southern plain, but the pattern was more heterogeneous than in Slovakia, and clusters of large and small fields occurred next to each other. Very small fields occurred often in the vicinity of larger settlements (Figure V-4).

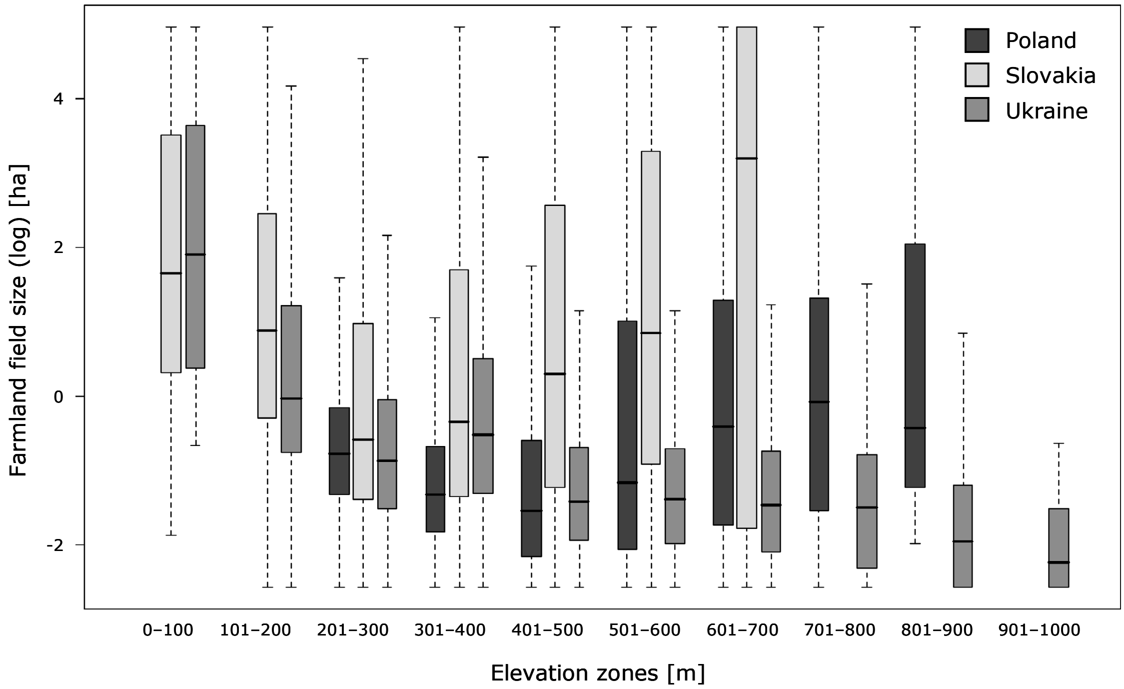

Figure V-6: Distribution of field sizes per elevation zone and country. Boxplot whiskers extend to 1.5 times the interquartile range.

Field size co-varied with altitude in all three countries (Figure V-6). In Poland, fields were smaller at low altitudes and increased with elevation. In Slovakia and Ukraine, field sizes were much larger at lower altitudes compared to intermediate altitudes. At higher altitudes, areas of small and large fields occurring side by side whereas field size consistently decreased along the altitudinal gradient in Ukraine, and the highest mountain valleys there displayed smallest field sizes (Figure V-6). Three field visits (summer 2004, spring 2005, and spring 2006) included all three countries and confirmed the plausibility of the land use patterns in our field size maps.

5 Discussion

5.1 Mapping parcelization using texture measures

We found a strong relationship between field size and Landsat TM/ETM+ texture measures and we used our models to map field size patterns for our full study area. We therefore suggest that texture measures bear considerable potential to map land use patterns and changes therein. This may be especially important in areas that are undergoing rapid change and where alternative data sources (e.g. cadastral maps) are not readily available or of unknown reliability, such as in Eastern Europe and the former Soviet Union.

Our predictions of field size varied based on the texture measures used, but some clear patterns emerged. As expected, the best predictors of field size were texture measures related to the local heterogeneity of grey level values. However, different texture measures quantify different aspects of this heterogeneity. We found measures that characterize the "orderliness" of an image (i.e. regular distribution of grey values, Hall-Beyer 2007), such as entropy and the second angular moment, to be most sensitive to variations in field size. Entropy measures the degree of disorder or textural uniformity of grey level values (1^{st}-order entropy) or grey level value pairs (2^{nd}-order entropy) (Anys and He 1995; Baraldi and Parmiggiani 1995; Anys et al. 1998). Angular second moment (sometimes also referred to as energy) is strongly, but inversely related to entropy, and measures the uniformity of an image (Haralick et al. 1973; Gong et al. 1992; Baraldi and Parmiggiani 1995). Farmland fields, patches of similar grey values, are often organized in distinct geometric patterns (e.g. along valleys, or perpendicular to roads to provide easier access to farmers). This likely explains why measures such as entropy and angular second moment predicted field size best.

Variance, correlation, and 1^{st} and 2^{nd}-order mean were, in addition to the above measures of orderliness, often included in the best multiple regression models (2 or 3 covariates). Variance describes the variability of grey level values within a given window (Haralick et al. 1973). In other words, variance directly relates to our underlying hypothesis that local heterogeneity is highest where small fields dominate. Correlation is a measure of grey level linear dependency in an image (Haralick et al. 1973) and uncorrelated to the measures of orderliness. Linear dependencies are characteristic for agricultural land use patterns (i.e. farmland fields are often rectangular), thereby explaining the sensitivity of the correlation feature towards field size. First and 2nd-order mean (the average or expected combination of two co-occurring grey level values within a window) both relate to purely spectral rather than textural characteristics. In univariate models, these measures predicted field size poorly. However, 1st and 2nd-order mean based on bands from the visible domain were frequently included in our best multiple regression models, likely because they provided additional information for separating soil and vegetation patches (i.e. fields in agricultural areas).

Some texture measures predicted field size poorly and were not included in any of the best models. Particularly, measures that quantify image contrast (e.g. dissimilarity, contrast, or homogeneity) yielded lower predictions than those measures that quantify the organization of contrasting features (i.e. image orderliness). The weak relationship of contrast measures and field size was not surprising, because the degree of image contrast is not related to particular land use patterns. Moreover, contrast measures are particularly sensitive to periodic features in an image (Baraldi and Parmiggiani 1995). In agricultural landscapes with many different crop types and bare fields, such reoccurring patterns are scarce. Other measures that were poor predictors of field size included statistical parameters that are not related to the spatial organization of grey-level values (e.g. histogram skewness).

Selecting an appropriate window size is a crucial step when characterizing image features based on texture (Anys and He 1995). Texture measures calculated using intermediate window sizes (e.g. 7, 9, or 15 pixels) yielded the best field size predictions (Table V-1 and Table V-2). At such window sizes, many small fields (e.g. in areas of subsistence farming) are found within a chosen window, and result in high local heterogeneity. Large fields on the other hand, were still relatively homogeneous at such window sizes. These differences translated into distinct textural characteristics that were useful to map field size (Ozdogan and Woodcock 2006). Most texture measures displayed a clear peak in predictions at these intermediate window sizes, and decreased rapidly for larger windows. This also indicated that the range of window sizes tested was sufficient.

Landsat bands in different spectral domains predicted field size differently. The short-wavelength infrared (SWIR) bands and the bands in the visible domain captured much of the variation in farm fields, making texture measures calculated from these bands highly suited for field size mapping. The SWIR bands are particularly sensitive to variations in moisture content, and are important for mapping agricultural areas, for separating senescent and green vegetation, and to differentiate soils types (Cohen and Goward 2004).

The visible bands are especially helpful to separate vegetation and bare soil. On the other hand, senescent vegetation and soils are spectrally relatively similar in the near-infrared domain, thus explaining the lower predictions from texture measures based on the NIR band. Predictions from texture measures calculated from the SWIR and visible bands were fairly comparable, suggesting that senescent vegetation/soil discrimination was more important than separating senescent and green vegetation to map field size in our case.

Several combinations of texture measures, Landsat TM/ETM+ bands, and window sizes resulted in comparable predictions of field size in both univariate and multiple regression models. This was expected, because some Landsat TM/ETM+ bands are highly collinear (Small 2004), several of our texture measures are strongly correlated (Baraldi and Parmiggiani 1995; St-Louis et al. 2006), and texture measures calculated using similarly sized windows did not differ substantially (Figure V-3). Being conservative in the number of covariates included in our models was therefore important. We used a maximum number of three covariates and the leaps procedure was effective in selecting only variable combinations that displayed a low degree of collinearity (e.g. correlation coefficients among the variables in the best 3-dimensional mean texture (group I) model were 0.20, 0.31, and -0.69). We suggest that the strong collinearity among some of our input variables did not hinder our methodology, but simply led to a higher number of models that predicted field size equally well. Predicting field size likely does not depend on the exact combination of texture measures, window sizes, and Landsat bands. This is an advantage for transferring our methodology to other regions, because testing all possible combinations of input parameters is not necessary to find a model with similar goodness-of-fit than the absolute best model. We also suggest that reducing the dimensionality of the feature space (e.g. principal component transformation) may not be necessary, because the leaps procedure effectively selects variable combinations that explain the total variance best. We tested our models using the first three principal components per image instead of the original six Landsat TM/ETM+ bands, but this did not improve model predictions (results not shown).

Model predictions were fairly stable for comparable input variable selections from different images throughout the year, particularly for multiple regression models that used standard deviation texture. For mean texture models, the autumn image (September) yielded higher predictions, likely due to the presence of green vegetation, senescent crops, harvested fields, and bare soil. This spectral diversity of crop types resulted in higher local heterogeneity where land use patterns are dominated by small fields, and therefore a possible explanation for better predictions compared to the June and August image, where crop types are spectrally more homogeneous. However, the difference in goodness-of-fit among models from different images was relatively small (i.e. difference in adjusted R^2 <0.06). Using combinations of input variables from different images did not improve model predictions substantially. We therefore suggest that a single image suffices to predict field sizes from texture measures.

Applying the multiple regression models fitted at the sample plot level to our full study area was successful (Figure V-4). Both, the two-dimensional and three-dimensional models, yielded comparable patterns of field size for our study area. A disadvantage was the log-transformed nature of the dependent variable, which exponentially amplified outliers in the texture measures (for example due to errors of commission in the water and settlement masks, etc.), particularly in the map generated from the three-dimensional model. Cutting the extreme ends of the field size distribution partly addressed this problem, but this approach requires expert knowledge regarding the possible range of field sizes. Unrealistically high and low field sizes in the map generated from the three-dimensional model may also indicate over-fitting. However only a very small fraction of the study area was affected (predictions of <0.01ha for ~3% of the study area; >300ha for ~2% of the study area) and the cross-validation results did not suggest over-fitting. The robustness of our multiple regression models was also confirmed by the low cross-validation errors.

Our results show that image texture is a useful tool to map field size for areas with a high proportion of mixed pixels as well as for areas with very large fields. The field size maps proved useful to identify land use patterns and to compare these patterns among countries. We therefore suggest that texture has significant potential to monitor agricultural intensification and changes in land use patterns in Eastern Europe and in other regions of the world. Because texture is easily derivable from raw image data, it may represent an important variable (Southworth et al. 2004; Turner 2005) to assess landscape structure and land dynamics based on the spatial domain, and to assess structural land cover modifications in human-dominated landscapes. Moreover, land use pattern information is important to understand the relationship of land tenure and land use change. Incorporating land use patterns in land use change models has so far largely been based on cadastral maps (Verburg 2006). Such data are unavailable in many regions in the world, particularly those that experience rapid land use change, and field size variables based on image texture may be a useful alternative.

5.2 Field size in the border triangle of Poland, Slovakia, and Ukraine

We found marked differences in field size among the Polish, Slovak, and Ukrainian region of our study area. The study area was part of the Austro-Hungarian Empire for approximately 150 years before 1914. During that time, land management was relatively homogeneous (Turnock 2002). Therefore today's differences in field size among countries likely originated in socialist and post-socialist times. In our case, these differences are related to land ownership patterns and land management in socialist times, combined with different strategies to re-privatize farmland and individualize land use in the post-socialist period.

Poland had the smallest field sizes, particularly in areas below 500m elevation. The reason is likely that Poland was the only Eastern European country where collectivization failed (van Dijk 2003; Lerman et al. 2004), small family farms persisted, and fields were never aggregated (Lerman et al. 2004). However, the exceptions were Polish mountain valleys, where border changes between the Soviet Union and Poland after 1947 led to a depopulation and the establishment of large-scale, state owned farms (Turnock 2002; Augustyn 2004). After 1990, private farmland changed little, whereas state land was auctioned off, set aside, or converted to forest (Augustyn 2004). Our results show the largest fields in the Polish part of our study area at altitudes above 500m, mostly clustered in the mountain valleys close to the border with Slovakia (Figure V-4).

In Slovakia, all farmland became collectivized in socialist times and small farms were dissolved into large-scale, state-controlled agricultural enterprises (Lerman 2001; Csaki et al. 2003). Although land owners retained the title to their land, land was managed by the state (van Dijk 2003; Lerman et al. 2004). After 1990, Slovakia privatized the agricultural sector and restituted farmland to former owners, but this has not led to widespread parcelization and farming often continues on large fields (Trzeciak-Duval 1999; Csaki et al. 2003). This is reflected in our results by the high share of large fields, particularly in the southern plains. In such areas, socialistic land use patterns were effectively preserved (Mathijs and Swinnen 1998). Likely explanations are the relatively slow pace of reform (Csaki et al. 2003) and Slovakia's land owners, who often chose to lease their land to the successor organizations of the former cooperatives (Trzeciak-Duval 1999; Lerman 2001). In Slovak mountain valleys household fields occur next to fields managed by large-scale agricultural enterprises. Moreover, farmland abandonment was widespread in Slovak Mountain valleys resulting in relatively large, homogeneous areas, thus explaining the occurrence of very large fields in these areas.

In Ukraine, we found heterogeneous patterns of field size, and strong differences between mountain valleys and the plains in the North and South. In socialistic times, all farmland in Ukraine was state-owned and managed in large-scale farming enterprises (Ash and Wegren 1998; Lerman 2001). After the breakdown of the Soviet Union in 1991, Ukraine chose to distribute farmland among the workers of the state farms and collectives (Lerman et al. 2004). Land reform, however, was slow and much of the farmland is still managed by large-scale successor organizations. As a consequence, we found clusters of large fields, particularly in the plains. Parcelization occurred in some areas (Ash and Wegren 1998; Lerman et al. 2004) and we found evidence of parcelization in the vicinity of larger settlements, where people use farmland for subsistence farming, and land is accessible and potentially more valuable. Mountain valleys were almost exclusively characterized by very small field sizes, because Ukrainian mountain valleys have a high population density, and many people depend on subsistence farming.

Studying land use patterns in areas that are undergoing political and economic transitions allows assessing the effects of changing institutions, land management policies, and land ownership on land change. Our method permitted the cross-border comparison of field size and land use pattern, and revealed marked differences among the Polish, Slovak, and Ukrainian regions of our study area. These differences are likely related to land ownership and land management in socialist times as well as dissimilarities in land reform strategies after 1990. Mapping these differences would not have been possible using traditional classification-based methods, and image texture proved to be a reliable continuous indicator to map structural land cover modifications, such as the parcelization of farmland in Eastern Europe. Texture may thus contribute to an improved understanding of the spatial extent, causes, and consequences of land cover modifications in other regions of the world as well.

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Chapter VI:
Synthesis

1 Summary and main conclusions

The first overarching goal of this thesis was to advance the understanding of broad-scale land use determinants by studying the natural experiment that occurred in Eastern Europe after the system change in 1990. The political, economic, and societal transition resulted in fundamental changes in the framework of underlying driving factors of land use decisions. Studying land cover dynamics in the post-socialist period therefore allowed for assessing of how such changes became manifested in landscapes. Cross-border comparisons were a useful approach to uncouple the effect of driving factors that changed similarly in all countries (e.g., economic conditions) from country-specific factors (e.g., different land reform strategies). Studying the border region of Poland, Slovakia, and Ukraine in the Carpathians, was particularly interesting, because it allowed for comparing the effects of the three different ownership patterns and land reform strategies that occurred in Eastern Europe after 1990.

<u>Research question I:</u> *Did the Polish, Slovak, and Ukrainian regions of the study area differ from each other concerning land use and landscape patterns?*

Chapter II clearly showed that the three countries took diverse pathways after the demise of the Austro-Hungarian Empire, resulting in marked differences in land cover and landscape patterns. Concerning forests, this became apparent in differences in forest cover (i.e., highest in Poland), the altitudinal distribution of forests (e.g., considerably lower forest cover in Ukraine at higher altitudes), forest composition (e.g., relatively high share of conifer plantations in Ukraine), and forest fragmentation (i.e., lowest in Poland). Agriculture was most abundant and less fragmented in Slovakia compared to Poland and Ukraine. In 2000, grassland dominated Polish and Slovak mountain valleys, whereas Ukrainian mountain valleys had a considerable share of cropland. Given the countries common history and the environmentally relatively homogeneous background of the region, these differences are most likely attributable to either socialist or post-socialist land use changes.

<u>Research question II:</u> *What were the changes in land use in the post-socialist period and did land use change differ among the three countries in the study area?*

Chapters III, IV, and V investigated the question whether post-socialist land use changes resulted in converging or diverging trends in terms of land cover and landscape pattern when comparing among the three countries in the study area. Land cover change was widespread between 1988 and 2000, and the forest change analysis, the farmland abandonment map, and the quantification of land use pattern clearly showed that trends differed considerably among the three countries. Overall, forest cover changes were relatively moderate in Poland and Slovakia, especially when including afforested areas that were most widespread in Slovak mountain valleys. In Ukraine, however, forest cover decreased, forests today are considerably more fragmented than in the late 1980s, and protected areas were less effective compared to Poland and Slovakia.

Concerning agriculture, the main result was widespread abandonment of farmland in all countries. Yet, the rates and spatial patterns of abandonment differed markedly, both among countries and when comparing different regions within countries (e.g., different altitudinal zones or land tenure regimes). Farmland abandonment was most widespread in Slovakia and on former state land in Poland, whereas relatively low abandonment rates were found in areas where subsistence farming dominated (e.g., Ukrainian mountain valleys, or areas where private farms dominated in Poland). These areas were also characterized by a highly heterogeneous landscape pattern with small fields, whereas the plains in Slovakia and Ukraine as well as some Polish mountain valleys were characterized by large fields. Generally, small fields indicating parcelization tended to occur in the vicinity of settlements, especially around larger cities (e.g., Uzhgorod, Mukacheve; see also Appendix A) and this zone of small-scale farming was often followed by a ring of abandoned farmland. Areas further away from larger settlements tended to become abandoned where population density was relatively low (e.g. Poland and Slovakia) and parcelized where many people depend on subsistence farming (e.g., Ukraine).

Overall, Poland and Slovakia showed a converging trend in the post-socialist period, characterized by already high or increasing forest cover in the foothill and mountainous zone, farmland abandonment in mountain valleys, and relatively low abandonment rates in the plains. In contrast, Ukraine clearly diverged from these two countries in terms of land cover and landscape pattern after the system change. Forest cover decreased, abandonment was relatively widespread at all altitudes, and human pressure in mountain valleys was considerable. This trend will likely amplify further in the future, because Poland and Slovakia are now members of the European Union with a uniform framework of land management policies and environmental standards.

What can be learned from the research in this thesis about the role of broad-scale political and socio-economic driving forces of land use change? Assessing post-socialist land use change in the border region of Poland, Slovakia, and Ukraine did not only emphasize the pivotal role of such driving forces for land use decisions, but also provided compelling evidence that widespread land use change is triggered where these boundary conditions change. Furthermore, this study showed that abrupt changes in driving forces immediately translate in rapid land use change. For example, economic depression, weakened institutions, and lower level of control explain the uniform pattern of increased forest harvesting in the first years of the transition period. Also, the rapidly decreasing profitability of agriculture under free-market conditions along with general population trends in Eastern Europe (i.e., migration of young people away from rural areas) resulted in the widespread abandonment of farmland, particularly were farming conditions are marginal.

Even more importantly, the cross-border comparisons carried out in this research allowed for separating out the effect of specific driving forces of land use change, particularly the role of changes in land ownership and land reforms. Land use change was more widespread where ownership patterns changed drastically. For instance, all other factors being equal, farmland abandonment rates were twice as high on former state land in Poland compared to areas that had always been in private ownership. Moreover, this study also underpins the importance of tenure stability (Geist et al. 2006). Farmland abandonment was lowest where land tenure was stable (i.e., private land in Poland) and highest where land tenure was insecure, for example where former owners were difficult to locate (e.g., Slovakia). Concerning forests, the findings in this study strongly support the assumption that neither state forestry (as in Poland and Ukraine) nor private forestry (as partly in Slovakia) are clearly better in lowering harvest rates and in guarding forest ecosystems. Rather the strength of institutions and the pace at which they are reformed is important, and good institutions tend to result in stable or increasing forest cover (Dietz et al. 2003; Tucker and Ostrom 2005).

Different land reforms resulted in markedly different outcomes concerning land use change. Restitution led to widespread abandonment in marginal areas (e.g., Slovak mountain valleys), because land disinterest among former owners was substantial. On the other hand, restitution practically preserved the large-scale socialist farming structure in areas where favorable farming conditions prevailed (see Csaki et al. 2003). Auctioning of farmland (i.e., former state-owned land in Poland) resulted in extensive set-aside areas, because most farmland was bought for speculative purposes. In contrast, abandonment rates were lower and parcelization was high where land was distributed, particularly in areas where people's livelihoods depend on subsistence agriculture (e.g., in Ukrainian mountain valleys).

The uniform environmental setting and the common history of the study area were important boundary conditions for comparing land use change across borders. Generalizing post-socialist land use trends observed in the border triangle of Poland, Slovakia, and Ukraine to areas outside the Carpathians or to the country level should be carried out with care. While much of the land use changes (and its driving forces) observed in the Polish, Slovak, or Ukrainian region of the study area may still be typical at the country level, a Carpathian study area can not account for the heterogeneity of environmental, societal, and economic conditions within a country.

The second goal of this thesis was to assess the fate of Carpathian ecosystems in the post-socialist period. Overall, human pressure has considerably decreased after the system change and many areas in the study area are essentially undergoing a process of rewilding. Farmland abandonment and land use extensification in rural areas provide opportunities for afforestation and increased carbon sequestration, and forest species may benefit from recent land use changes, particularly area demanding top herbivores and carnivores. However, farmland abandonment will likely decrease Carpathian biodiversity in the long run as landscapes characterized by low-intensity land use in mountain valleys are diminishing (Baur et al. 2006). Moreover, increased fragmentation of mature forests is of growing concern, particularly in the Ukrainian Carpathians where illegal logging is coupled to corruption, similar to other regions of the world (Buksha et al. 2003; Geist et al. 2006; WWF 2007).

The findings of this study underpin the essential role of broad-scale underlying driving factors on local land use decisions. Because changes in the framework of broad-scale land use determinants affect many land managers, resulting land use changes are widespread and may have a strong effect on earth system functioning when aggregated to regional or global scales. For example, farmland abandonment was widespread in all three countries and probably occurred at similar rates in other areas of Eastern Europe and the former Soviet Union, too (Peterson and Aunap 1998; Ioffe and Nefedova 2004; Baur et al. 2006; Müller and Munroe 2007). This study showed that much of these lands will revert back to forests, and this may have a profound effect on regional carbon balances. Broad-scale boundary conditions for land use decisions are likely equally important in other parts of the world where institutional and socio-economic change occurs more slowly. Interpreting the institutional and socioeconomic transition that occurred in Eastern Europe as a natural experiment provided useful insights into the relative importance of some of these boundary conditions. Such insights are urgently needed to guide decision makers in designing a policy framework that balances trade-offs between immediate human needs and the long-term capacity of the earth system to provide humanity with multiple ecosystem services (Foley et al. 2005; Bennett and Balvanera 2007; Kareiva et al. 2007).

2 Future research

Several interesting research issues for follow-up research beyond the scope of this work evolved during the course of this thesis.

Assessing post-socialist land use change in the Romania part of the Carpathians would significantly broaden the picture of how Carpathian ecosystems changed since 1990. An initial case study suggested that farmland abandonment may be equally widespread in this part of the Carpathians, whereas forest disturbance was overall relatively low (Kuemmerle et al. 2007b; Müller et al. 2007). Further research is certainly needed to gain a better understanding of land use trends in this part of the Carpathians, too. Similarly, studying post-socialist land use change for the Carpathians as a whole at sufficiently detailed scales would allow for improved assessments of habitat fragmentation and connectivity, and therefore for better assessing the consequences of land use changes for Carpathian wildlife and biodiversity. Moreover, an area-wide study of the Carpathians would facilitate comparisons of land change mapped from remote sensing images with official logging statistics that are often only available at highly aggregate levels. The discrepancy between these two data sources to assess forest change was one of the surprising results of this study and may be an important indicator of illegal logging in the region.

This study focused on quantifying land cover and landscape pattern change, and on qualitatively linking observed changes to its underlying drivers. A quantitative assessment of the underlying causes of land use change can give useful insights (see for example Müller and Sikor 2006; Müller et al. 2007). Yet gathering the necessary datasets for statistical model building in a border region with three countries would have been beyond the scope of this work and should be subject to future research. Moreover, it would also be interesting to extend observed land use trends into the future and to develop alternative land use scenarios for the Carpathians under consideration of different policy and economic environments (Verburg et al. 2006b; Westhoek et al. 2006).

On a technical level, a few issues show potential for further investigations. First, Riitters' (2002) indices were useful to compare forest fragmentation among countries, but interpreting their ecological importance is challenging. Advancing Riitters concept based on morphological image processing is a promising research direction and should allow for a better linkage of landscape pattern and ecological processes (Vogt et al. 2007a; Vogt et al. 2007b). Second, the disturbance index concept (Healey et al. 2005) could be extended by developing a method to derive thresholds separating disturbed from undisturbed forests. Also, testing the sensitivity of the disturbance index to the initial normalization step will be important. Both issues would certainly break a path for the more widespread use of this method (Healey et al. 2005). Third, support vector machines have great potential for becoming a standard method for complex multitemporal classification problems. Their strongest advantage is the relatively small number of trainings samples required, while still being able to handle complex class distributions. Testing the SVM approach for different problems and evaluating the minimum number of training samples needed to derive robust classifications would greatly improve the applicability of this method. Last, this thesis showed the usefulness of image texture for mapping changes in land use pattern and field size. Initial tests indicated that texture may be image inherent, and that transferring statistical models among images and time periods may be difficult. Combining the quantitative modeling approach presented in Chapter V and the segmentation-based classification detailed in Appendix A may be a promising way of making use of the potential of both approaches.

Generally, this study showed the great potential of studying natural experiments to better understand the drivers of land use change. In Eastern Europe, the next natural experiment has already occurred with the accession of 10 former socialist countries to the European Union. These countries now comply to extensive environmental regulations, adopt new land management policies, and benefit from the agri-environment schemes of the European Union. Studying how Eastern Europe's landscapes change under such fundamentally changing boundary conditions for land use decisions will be interesting. For example, much of the abandoned or set-aside land may be put back into production to receive subsidies. At the same time, increased urbanization and migrations from East to West may lead to increased abandonment rates. Assessing this natural experiment will give invaluable insights into the drivers of local land use decisions, particularly when comparing socialist centralized economies, the free-market period, and EU market conditions. This may ultimately contribute to both, an improved understanding of the coupled human-environment system, and a more detailed picture of ecosystem dynamics in this understudied region.

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Appendix A:
Mapping post-socialist parcelization of farmland in Eastern Europe using texture measures

Proceedings of the 2nd Workshop of the EARSeL Special Interest Group on Remote Sensing of Land-Use & Land-Cover, 28th-30th September 2006, Bonn, Germany [online publication]

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1 Introduction

Land use is an important driver of global environmental change and has resulted in widespread degradation and loss of ecosystem structures and services (Foley et al. 2005). Monitoring land-cover change and assessing its drivers is therefore of great international concern (Gutman et al. 2004; Lambin and Geist 2006), but the understanding of how people influence land change is still far from complete (Rindfuss et al. 2004). Remote sensing is the most important tool to provide information on where land changes occur (Lambin and Geist 2006). Traditional methods to quantify land change from multitemporal remote sensing images often rely on classifying the image into discrete land cover classes, or alternatively into change classes (Lu et al. 2004). Although these methods are useful to assess land cover conversions such as deforestation or urbanization, they potentially overlook changes in within-class heterogeneity (Coppin et al. 2004). This is unfortunate, because modifications of land cover are widespread. Consequently, there is an urgent need for developing robust and repeatable change detection methods that rely on continuous rather than discrete data, and thus allow for monitoring land cover modifications (Southworth et al. 2004).

Following the Fall of the Iron Curtain in 1989, Eastern European countries transitioned from planning economies to market oriented systems. This transition has drastically affected land management and land use decisions, and resulted in widespread land cover changes, such as the abandonment of farmland (Peterson and Aunap 1998), and changes in forest cover (Augustyn 2004; Bicik et al. 2001). Moreover, the transition has triggered modifications of land cover and changes in landscape pattern, particularly concerning farmland. Before 1990, most of Eastern Europe’s farmland was managed by the state in large-scale agricultural co-operatives. Since 1990, all Eastern European countries have implemented land reforms to break up the large-scale farming structures and to privatize the agricultural sector (Lerman et al. 2004). These land reforms, in combination with inheritance practices and the underlying ownership pattern, resulted in a split-up of the large socialistic fields into smaller parcels, and led to the physical fragmentation (hereafter called parcelization) of farmland in many areas (Sabates-Wheeler 2002; van Dijk 2003). Land reform strategies differed strongly among Eastern European countries. However, not much is known about the extent and spatial pattern of post-socialist parcelization and it remains largely unclear how different land ownership structures and land reforms affected the parcelization of farmland in Eastern Europe.

We selected the border triangle of Poland, Slovakia, and Ukraine because all three countries had different land ownership patterns and land management policies in socialist times (Table A-1), which in turn led to different land reform strategies after the system change (Augustyn 2004; Lerman et al. 2004). Moreover, the region was part of the Austro-Hungarian Empire for a period of around 150 years before 1914 with relatively homogeneous land management (Turnock 2002). Differences in farmland parcelization among countries are therefore likely due to either socialist or post-socialist land management (Kuemmerle et al. 2006), making the area particularly well suited to study the effects of land reforms on parcelization.

Table A-1: Land ownership of agricultural land and privatization strategies of the countries in the study area (Lerman et al. 2004).

Country	Land Ownership Before 1990	Potential Private Land	Privatization Strategy	Land market
Poland	Private and state owned	All	Sell state land (plots)	Buy/sell, lease
Slovakia	Collectivized (cooperatives)	All	Restitution (plots)	Buy/sell, lease
Ukraine	State owned	All	Distribution (shares)	Only lease until 2005

Monitoring and quantifying parcelization is challenging, because statistical or cadastral data often do not exist, or data are of limited or unknown liability (Filer and Hanousek 2002). Using remote sensing images is promising because consistent data from before and after 1990 exist, but studying parcelization requires the quantification of changes in the structural pattern within farmland. Image texture measures are interesting to address this challenge, because texture measures capture the spatial and structural arrangement of image objects by quantifying the spatial variability of grey levels within a local neighborhood (Haralick et al. 1973). As such texture measures can be used to characterize heterogeneity within land cover classes (St-Louis et al. 2006), and may be well suited to quantify the parcelization of farmland in Eastern Europe. In summary, we were interested in assessing the extent and spatial pattern of post-socialist farmland parcelization in the border triangle of Poland, Slovakia and Ukraine. Our specific objectives were to:

(1) develop a method that allows for quantifying changes in the parcelization of farmland using texture measures and Landsat Thematic Mapper (TM) / Enhanced Thematic Mapper Plus (ETM+) images, and to

(2) compare parcelization among countries to assess whether different land reforms resulted in different parcelization rates.

2 Data & Methods

Our analysis was based on three Landsat images, representing spring, summer, and early autumn, for each of the two time periods 1985-88 (before the system change) and 2000 (10 years after the system change). We used 4 Landsat TM images (30th April 1985, 2nd October 1986, 27th July 1988, and 21st August 2000) and 2 Landsat ETM+ images (6th June 2000, and 30th September 2000) from path 186 and row 26. All images were co-registered and corrected for relief displacement using a semi-automatic method (Hill and Mehl 2003) and the SRTM digital elevation model as a base map (Kuemmerle et al. 2006a). The TM and ETM+ data were atmospherically corrected using calibration coefficients and a modified 5S radiative transfer model that incorporated a terrain dependent illumination correction (Hill and Mehl 2003).

Forests were masked out using unsupervised clustering (see Kuemmerle et al. 2007). The three images for each time period were stacked and transformed into principal components to emphasize phenological differences between the images, to enhance the signal to noise ratio, and to reduce storage space and computation time. We retained principal component 1-8 and carried out image segmentation on each image stack separately using a region-growing algorithm (Baatz and Schäpe 2000). Texture measures were calculated for each segment and we gathered a set of representative samples for the two classes "high parcelization", and "low parcelization" based on field visits and very-high resolution data (3 IKONOS images and 14 Quickbird images were available for these purposes). The segmented images were then classified using texture measures and the maximum likelihood classifier to derive parcelization maps for the two time periods. We used post-classification comparison of these parcelization maps to delineate a change map and summarized parcelization changes for our study area.

3 Results & Discussion

Agricultural parcelization differed markedly among the countries Poland, Slovakia, and Ukraine in socialist times, likely due to different ownership patterns that in turn led to different land reforms. In Poland, much of the farmland was privately owned even before

1990, resulting in smaller farm sizes and parcels, and thus in a high share of highly parcelized land (Figure A-1). Slovakia was dominated by large parcels, because all agricultural land was managed in large-scale co-operatives. In Ukraine, a heterogeneous pattern of large-scale and fine-scale agriculture was observed in the lowland areas. The mountain valleys showed a highly parcelized farmland pattern already before 1990 (Figure A-1), because population density is high in these areas and many people depend on subsistence farming (Augustyn 2004; Turnock 2002).

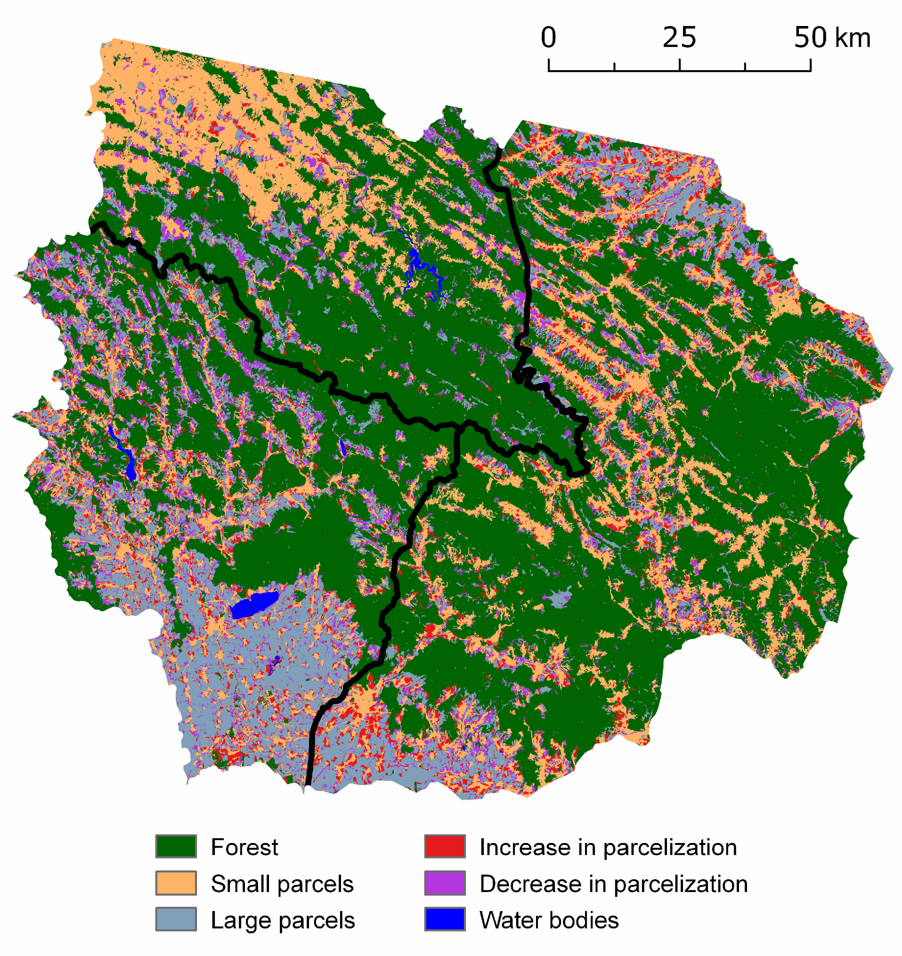

Figure A-1: Changes in the parcelization of farmland in the border region of Poland, Slovakia, and Ukraine (UTM reference system with WGS84 datum and ellipsoid).

Concerning changes in parcelization in the post-socialist period, Poland did not experience much change, because ownership did not change substantially (Lerman et al. 2004), except for some areas close to the border to Slovakia where state farms managed all land. On the other hand, the land use pattern changed considerably in Ukraine and Slovakia. In Slovakia, the share of large parcels was still very high in 2000, suggesting that the large-scale agricultural enterprises still managed most of the land, although cooperatives were transformed into private enterprises (Lerman et al. 2004). Most of the farmland was restituted to former owners; yet, these owners often chose to lease their land back to the cooperatives (Lerman et al. 2004). Some parcelization occurred, mainly close to settlements in the south of the study area. In Ukraine, where land was distributed among the workers of the cooperatives much of the land became parcelized in post-socialist times, in particular farmland close to settlements, and especially close to the cities of Uzhgorod, Mukacheve and Sambir (Figure A-1). Decreases in parcelization occurred mainly in mountain valleys and are possibly connected to the abandonment of farmland due to outmigration from these regions.

4 Summary & Outlook

This research demonstrated that image texture can be a useful tool to map farmland parcelization and to quantify modifications within land cover classes. Our results showed distinct differences in parcelization among the three countries in our study area. In Poland, not much has changed, because private land ownership existed before 1990. Where land reforms were implemented, they led to marked changes in parcelization. Changes were strongest in Ukraine, where land was distributed among the people, whereas restitution in Slovakia partly preserved the large-scale farming sector because many owners leased their land to agricultural enterprises. Further research is required to quantitatively link parcel size and texture measures, and to validate parcelization changes based on high-resolution remote sensing data, aerial images, or cadastral maps.

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Appendix B:
A method to detect and correct single-band missing pixels in Landsat TM and ETM+ data

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Abstract

Human land use is the main driver of terrestrial ecosystems change, and remote sensing is an important tool to monitor these changes. Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) images have been the most important data source to map land cover change, but image artifacts often hinder or even prohibit digital change detection. This paper addresses a group of image distortions that display erroneous values in a single band while the leaving the other bands of a spectrum undisturbed. Such artifacts may be due to different phenomena, for instance transmission and ground processing problems or single event upsets. Automated artifact detection for those phenomena is often difficult, because erroneous band values often lie well within the range of naturally occurring radiance values. We developed IDL-based software that uses edge operators to detect and label affected pixels. Using a least squares spectral matching algorithm, the distorted spectrum is compared to undisturbed spectra in the local neighborhood and the undisturbed spectrum of best fit is determined. The erroneous band value is then replaced with the corresponding undisturbed value. This method was tested on seven Landsat TM images and on artificial data. Our results show that the distorted areas are precisely detected and that the correction procedure leads to meaningful spectra. This approach may be useful to minimize the effect of single-band distortions and allows for subsequent image analysis without the need to mask out distorted areas. The software tool includes a user interface and is available online.

1 Introduction

Anthropogenic land use is the main driver of terrestrial ecosystem change and results in widespread degradation and loss of ecosystem structures and functions across the globe (Foley et al. 2005). Monitoring land cover change, understanding its underlying causes, and assessing the consequences of human land use for ecosystems and biodiversity is therefore of great international concern (Gutman et al. 2004; Lambin and Geist 2006; Rindfuss et al. 2004). Remote sensing is the key technology to assess the extent and rate of land cover change (Lambin and Geist 2006; Rindfuss et al. 2004). Among the numerous earth observation satellites that are operating today, data from the Landsat Thematic Mapper (TM) 4 and 5, and the Enhanced Thematic Mapper Plus (ETM+) instruments are particularly well suited to address ecosystem dynamics. The sensors have a swath width of 185km, a spatial resolution of 30m, and six spectral bands in the visible, near- and shortwave-infrared domains (centered at 0.49, 0.56, 0.66, 0.83, 1.65, and 2.22µm, respectively). More importantly, a unique and continuous data record of Landsat images exists for the majority of the Earth's land mass (TM-4 was operational between 1982 and 1993, TM-5 between 1984 and today, ETM+ between 1999 and today; all with a 16-day repeat cycle). Because of these properties, Landsat images continue to be the most important data source for monitoring land change at fine to medium scales (Cohen and Goward 2004; Goward and Masek 2001). Landsat data have been widely applied to assess land cover change, such as mapping tropical deforestation (Dale et al. 1993; Skole and Tucker 1993), desertification (Palmer and van Rooyen 1998), and urban growth (Seto et al. 2002; Ward et al. 2000). The research presented in this paper was carried out within the scope of several land-cover change projects focusing, for example, on Mediterranean land degradation (Hostert et al. 2003; Kuemmerle et al. 2006b) and forest mapping in Eastern Europe (Kuemmerle et al. 2006a).

Thorough pre-processing of Landsat imagery is necessary to enable multitemporal comparison and to derive accurate change maps. This usually consists of four stages: (A) correction of systematic effects such as the scan time skew, earth curvature effect, and panorama distortion, (B) radiometric calibration to convert digital numbers to at-satellite radiance (the radiant flux from a given area in the sensor's instantaneous field of view and for a specific wavelength; measured at the sensor in W m^{-2} sr^{-1} μm^{-1}), (C) atmospheric and topographic correction to minimize topographic influence and to attain surface reflectance, and (D) geometric correction to ortho-rectify the images. While the user has full control over stages (B), (C) and (D), the correction for systematic effects is usually carried out by the data provider (e.g. the United States Geological Survey (USGS) or Eurimage).

Additional pre-processing steps may be required if the data contains distortions or image artifacts. A multitude of phenomena are known to cause spectrally distorted pixels in Landsat TM and ETM+ images. Distortions may occur during the recording of an image or they may be introduced in the processing chain of the data vendor. Visual image analysis can compensate for these distortions to some extent, because cognitive interpretation always includes context information (e.g. spatial neighborhood information). However, image artifacts may drastically hinder automatic image analysis. This is problematic for digital change detection methods that commonly rely on the spectral comparison of a pixel at two different time stages, particularly if the images must be standardized or transformed prior to the change analysis (e.g. Tasseled Cap Transformation, NDVI calculation, etc.). Examples of such methods include image differencing, image ratioing, composite analysis, or change vector analysis (Coppin et al. 2004; Lu et al. 2004). Distorted pixels often result in the detection of pseudo-change, which can hamper or even inhibit the interpretation of the change map and the derivation of change statistics. Masking out affected areas manually is a solution, but leads to no-data areas in the change map, which is problematic for studies that address landscape pattern (e.g. forest fragmentation Kuemmerle et al. 2006a; Riitters et al. 2002). Moreover, selecting distorted pixels manually is not feasible if they are frequent or distributed over large areas. In such situations, distorted pixels need to be detected automatically and, if possible, corrected before digital change detection is carried out.

One type of image distortion common to system-corrected Landsat TM and ETM+ scenes involves individual pixels with an erroneous value for a single spectral band, while the other bands remain undisturbed. Only a minority of the erroneous band values saturates low or high and the values of the distorted pixels often are well within the range of realistic image values. The automated detection of missing pixel distortions is therefore challenging and simple threshold operations are not appropriate. A possible solution is the use of local filter operations. Erroneous band values always deviate considerably from the undisturbed values in their vicinity, thereby causing a so-called "hard edge" in brightness values in the image. Edge filters can pick up these local differences in the brightness function (Richards and Jia 2005), and by comparing edge filter images of different bands, it is possible to separate "natural" edges from edges introduced by single-band distortions.

Correcting single-band missing pixel distortions is not an easy task, because the magnitude of the distortion (i.e. the offset between the original and the erroneous band value) is unknown. However, the five undisturbed band values of a distorted pixel hold a substantial amount of spectral information that can be used to find similar, but undisturbed spectra in the local neighborhood of the distorted pixel. Erroneous band values can then be replaced using the corresponding band values of a spectrally similar pixel, thereby lessening the effect of single-band distortions, or in best case restoring the undisturbed image spectra.

The overarching goal of this study was to mitigate and correct single-band distortions in Landsat TM and ETM+ data for subsequent image processing. Our specific objective was to develop a methodology that allows for (I) the detection of distorted pixels using edge filters, and (II) finding undisturbed spectra that closely resemble the distorted spectrum to replace erroneous band values.

2 Background

Missing or distorted pixels have frequently been reported to occur in the bands of the reflective domain of Landsat 4 and 5 TM instruments, and the Landsat ETM+ sensor (Helder and Ruggles 2004; Irish 2006; Saunier 2005; USGS 2006). Generally, distorted pixels can be grouped into two categories: (A) artifacts that arise from internal and external sensor anomalies during the scanning of an image and (B) artifacts introduced during the pre-processing chain of the data vendor. Distortions of type A have been discussed in the literature. Helder and Ruggles (2004) show three common radiometric artifacts, specifically the scan-correlated shift, memory effect, and coherent noise, and give advice concerning the correction of these effects. In particular the removal of striped artifact patterns known as banding or striping, which may arise from memory effects or mis-calibrated detectors, has received special attention, and various methods have been developed to correct such distortions (Gadallah et al. 2000; Helder and Ruggles 2004; Poros and Peterson 1985; Srinivasan et al. 1988). Errors of type B are not very well documented and often only in grey literature, such as data handbooks and internal handling guidelines, exists (Irish 2006; Saunier 2003, 2005).

In this study, we address Landsat TM an ETM+ image distortions that have not received much attention. These distortions can be described as pixels with obviously false or missing values in a single spectral band for a given pixel (Saunier 2003). The erroneous band value is characterized by positive or negative deviations from the actual radiance value compared to the "true" radiance values, sometimes resulting in over- or under-saturation. The Earth Observation Quality Control (EOQC) of the European Space Agency (ESA) has named the phenomenon "missing pixels effects" (Saunier 2003). Figure B-1 shows examples of such distorted pixels.

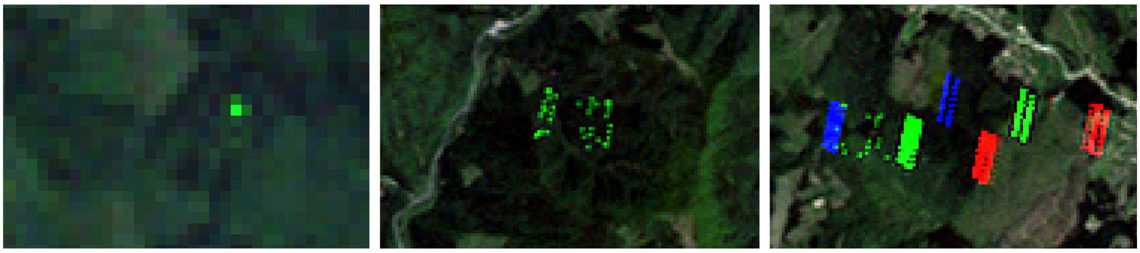

Figure B-1: Three different kinds of distortions occurring in Landsat TM data. Left: only a single pixel is affected; middle: several pixels affected and random pattern of distorted pixels can be observed; right: distorted pixels are clustered and the affected show a detector pattern (all distortions occurred in a Landsat 5 TM image, acquired 4th July 1994).

A wide variety of patterns of missing pixel distortions may be observed. Generally, the phenomena may be clustered into three groups (A) single pixels with erroneous values spread out in a random pattern, which are very hard to detect visually (Figure B-1, left), (B) irregularly shaped clusters (Figure B-1, middle), and (C) a rectangular detector pattern (Figure B-1, right). Although distortions occur only in a single band for a given pixel, all optical bands of an image may be affected by the distortions, often resulting in a typical sequence of image artifacts along the scanning track of the sensor.

In most cases, only a few pixels are affected within a scene. However, image distortions may be scattered throughout the whole image and a large number of pixels may be damaged. The origin of these artifacts is not clear in all cases and an intensive discussion of sensor and pre-processing chain related image distortions is beyond the scope of this paper. However, some of the possible causes for the missing pixel phenomenon may be summarized as follows:

Sticky bits

During the recording scan, one or more bits keep their previous value instead of switching to 1 or 0 respectively. This results in an increase or decrease of the "real" digital number by a value of 2^N, where N is a number between 0 and 7 (Saunier 2003).

Tape degeneration and transmission problems

Pixels or clusters of pixels may be missing due to acquisition problems or tape degradation. This problem is often reported as occurring coincidentally with other anomalies, such as data framing errors that produce scan line shifts/offsets (ESA 2003).

Ground processing problems

Pixels may become distorted during the ground recording or pre-processing of systematic effects. Cases have been reported where a scene containing missing pixel errors (e.g. dropped scans) was found to be error-free when ordered through a different data provider (G. Chander, pers. comm.). It also has been suggested that the missing pixels phenomena may be connected to old processing chains (i.e. before 1999) (Saunier 2003).

Single event upsets

A Single Event Upset (SEU) occurs when an energetic particle travels through a transistor substrate and causes electrical signals within the transistor. SEUs have been reported as often occurring in near-earth orbit when the satellite passes through the Van Allen belts (a ring of energetic charged particles around Earth, trapped by the Earth's magnetic field), especially the northern and southern auroral zones and the South Atlantic anomaly. The anomalies take the form of one or more sudden bright pixel in response to the high energy particle traveling through the transistor substrate. After the initial bright spike there are one or more dark pixels as the affected detectors recoil in bright target recovery (USGS 2000).

Although the exact sources of the missing pixels phenomena might remain unclear, it is important to mention that the effects resulting from these phenomena are similar. Thus, the method to detect and correct distorted pixels proposed in this research will work for all of these distortions, regardless of their origin.

3 Methods & Materials

3.1 Data

A total of seven Landsat TM scenes were used in this study to develop a method to detect and correct single-band missing pixels. Six images displayed such distortions, and the number of affected pixels ranged between 3,600 and 180,700. The image without distortions was used for validation purposes (see below). All images were acquired over different regions in Europe between 1984 and 1994 (Table B-1).

Table B-1: Landsat TM images used in this study and the number of pixels affected by missing pixels distortions.

Path	*Row*	*Sensor*	*Region*	*Acquisition Date*	*Affected Pixels*
186	026	TM 5	Eastern Europe (SE Poland)	4th July 1994	~ 108,700
186	026	TM 5	Eastern Europe (SE Poland)	7th June 1994	~ 65,400
181	035	TM 5	Southern Europe (Crete, Greece)	24th May 1986	~ 10,000
186	026	TM 5	Eastern Europe (SE Poland)	27th July 1988	0
193	023	TM 5	Central Europe (Germany)	29th April 1987	~ 42,700
188	032	TM 5	Southern Europe (Italy)	20th June 1984	~ 44,488
203	034	TM 5	Southern Europe (Portugal)	13th April 1985	~ 3,646
196	026	TM 5	Western Europe (Germany)	30th July 1984	~ 9,912

3.2 Methods

We developed software based on the Interactive Data Language (IDL) and equipped it with a user interface (using IDL 6.0, RSI 2003). The software minimizes the effects of missing pixel distortions in Landsat images for subsequent image processing. Our methodology consisted of two stages. First, distorted pixels were detected in an automated way using edge operators. The edge filter images from different bands were then compared to separate single-band edges (i.e. edges introduced by single-band missing pixels) from multiple-band edges (i.e. natural edges). Second, we used a spectral matching procedure to find similar, but undisturbed pixels in the neighborhood of the distorted pixels. The spectrum of closest fit was used to restore the erroneous band value in the distorted pixel, thereby allowing for subsequent image processing such as digital change detection.

Stage I: Detection of distorted pixels

Edge detection operators commonly determine the magnitude of the gradient ∇ of the continuous brightness function $\Phi(x,y)$ to determine hard edges in an image (Richards and

Jia 2005). The magnitude of ∇ is defined by the partial spatial derivatives ∇_1 and ∇_2 (Eq. 1).

$$|\nabla| = \sqrt{\nabla_1^2 + \nabla_2^2} \quad (1)$$

For continuous data, ∇_1 and ∇_2 are determined using Eq. 2.

$$\nabla_1 = \frac{\partial}{\partial x}\Phi(x,y),\ \nabla_2 = \frac{\partial}{\partial y}\Phi(x,y) \quad (2)$$

However, for discrete image data consisting of rows and columns, ∇_1 and ∇_2 are equivalent to simultaneous applications of a moving-window template in x and y direction (Richards and Jia 2005). The Roberts filter is an easy-to-compute edge-detection operator that uses two 2x2 convolution masks (Eq. 3) to estimate ∇_1 and ∇_2 (RSI 2003).

$$\nabla_1 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \ and \ \nabla_2 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad (3)$$

The Roberts operator is highly sensitive to noise, because only a very small number of pixels are used to approximate the gradient. This is usually disadvantageous, if natural edges are to be delineated, as more advanced operators with larger convolution masks are better suited for such applications. However, to detect distorted pixels, the noise sensitivity proved to be advantageous and the Roberts filter performed better than more complex operators (e.g. Canny, Prewitt, or Sobel).

Edges caused by single-band missing pixels differ from natural edges by characteristically only occurring in one image band for a certain position (i.e. a pixel). To investigate whether edges occur in multiple bands or just in a single band, band ratios were used. This concept utilizes the fact that most TM bands show a moderate to high degree of collinearity to neighboring TM bands, for instance, the three bands in the visible domain are usually highly correlated (Small 2004). To separate data artifacts from natural edges, we empirically derived band-ratio thresholds for bands that were expected to be correlated, and compared them to the band that contained the distortions (e.g. band 1 was compared with the ratio of band 1 / band 2).

While intercorrelated bands exist for the visible and shortwave-infrared domain of the Landsat TM sensors, the procedure had to be adapted for the near infrared (NIR) band (TM band 4), because some natural features only show distinct edges in this domain (e.g. edges between vegetated and non-vegetated areas). We used a moving-window Laplacian filter to identify distorted pixels in the NIR band, although relying on a single-band in the detection procedure may result in lower detection accuracies (refer to the discussion section for details). The Laplacian operator computes the second derivative to detect edges (RSI 2003). In the two-dimensional case, it is defined as the sum of the partial derivates (Eq. 4).

$$\Delta = \frac{\partial^2}{\partial x^2}\Phi(x, y) + \frac{\partial^2}{\partial y^2}\Phi(x, y) \quad (4)$$

For discrete image data, this is equivalent to the application of a moving-window kernel (V). We used a 3 x 3 kernel (Eq. 5) to approximates the second order derivative and to detect edges in the NIR band (RSI 2003).

$$V = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \quad (5)$$

To ensure that all damaged pixels are processed in the correction procedure, the program allows for the inclusion of a user-defined buffer around the detected image distortions. A buffer of 5 pixels proved sufficient for all images used in our study.

Stage II: Correction

Correction of distorted areas by standard operations such as low-pass or median filtering proved inappropriate because the affected areas were regularly too large. An alternative is to make use of the high degree of spatial autocorrelation that is found in Landsat images (Chica-Olmo and Abarca-Hernandez 2000; Curran and Atkinson 1998). Because real-world objects at the landscape scale are usually bigger than a single Landsat pixel, there is a high probability that a similar, but undisturbed spectrum occurs in the local neighborhood of the distorted pixels. Once such undisturbed spectra are located, they can be used to correct the distorted spectra. To find such spectra, we compared the distorted spectrum to all undisturbed spectra (i.e. all spectra not labeled in the detection procedure) that were within a defined neighborhood. For the images used in our study, a neighborhood of 100x100 pixels proved to be a good compromise between computational cost and the quality of the correction results (note that users can adjust the extent of the neighborhood in the software). As a measure of fit, we calculated the root mean squared sums (RMS) of the band-wise differences between the spectra containing the erroneous band (u_i) and the band values (vi) of a given undisturbed neighborhood spectra (j) (Eq. 6, where i denotes a given undisturbed band, and k is the total number of undisturbed bands). The band containing the erroneous value was not considered in this calculation. The spectrum of closest fit was then defined as the spectra with the minimum RMS (RMS_{min}, Eq. 7).

$$RMS(j) = \sqrt{\frac{1}{k}\sum_{i=1}^{k}\left(v_{ji} - u_i\right)^2} \quad (6)$$

$$RMS_{\min} = \min_j(RMS(j)) \quad (7)$$

To correct the single-band missing pixels we then substituted the erroneous band value with the corresponding value of the RMS_{min}-spectrum.

Validation

Validating the effectiveness of a method to detect and correct single-band missing pixels is challenging, because the original, undisturbed values of the erroneous bands remain unknown. We therefore artificially introduced erroneous band values to nine undisturbed areas of the Landsat TM image from 4th July 1994 and tested our methodology (developed on real distortions) on these simulated distortions. Only the error-affected band values were replaced while all other band values of the original spectra remained unchanged. Altogether, 9,117 image spectra were artificially disturbed. To test our methodology, we located and corrected those pixels using our methodology and compared the corrected band values with the original, undisturbed band values. This was done by calculating the minimum, maximum, and average deviation, the standard deviation, the root mean squared error (RMSE, Eq. 6) and the confidence interval limits ($p<0.01$) of deviations between original and corrected band values.

To further test the usefulness of our correction procedure for subsequent change detection, we derived the normalized difference vegetation index (NDVI) and Tasseled Cap brightness, greenness, and wetness indices (Crist and Cicone 1984) for disturbed and corrected images, because both NDVI calculation and Tasseled Cap transformation are frequently carried out prior to digital change detection (Coppin et al. 2004). All calculations were carried out for a study area in the Ukrainian Carpathians (based on the image from 4th July, Table B-1). In addition, we applied three common change detection methodologies to detect forest change for our Carpathian study area using an undisturbed image from 1988 and both, the disturbed and the corrected image for 4th July 1994 (Table B-1). We used image ratioing on the raw TM images, differencing of NDVI images

(Coppin et al. 2004; Lu et al. 2004), and the recently developed forest disturbance index based on Tasseled Cap transformed imagery (Healey et al. 2005). For all three change detection methods, we applied a threshold to classify the continuous change map into a binary change/no-change map. The same threshold was used for the change map derived using the disturbed image and the change map calculated using the corrected image. In the case of image ratioing, the sum of the band-wise change maps was calculated to derive a binary change/no-change map.

4 Results and Discussion

The automatic detection algorithm based on edge filter images (using the Roberts operator for the visible and shortwave infrared (SWIR) bands and the Laplace operator for the NIR band) was very efficient in separating areas that were distorted by single-band missing pixels (Figure B-2). Even missing-pixels distortions that would be hard or impossible to detect visually were revealed by the detection algorithm. Such distortions include single pixels, unsaturated pixels or pixels with relatively low contrast with respect to their neighborhood, and artifacts in heterogeneous areas. Deviations between erroneous and corrected band values were substantial and varied considerably (Figure B-3).

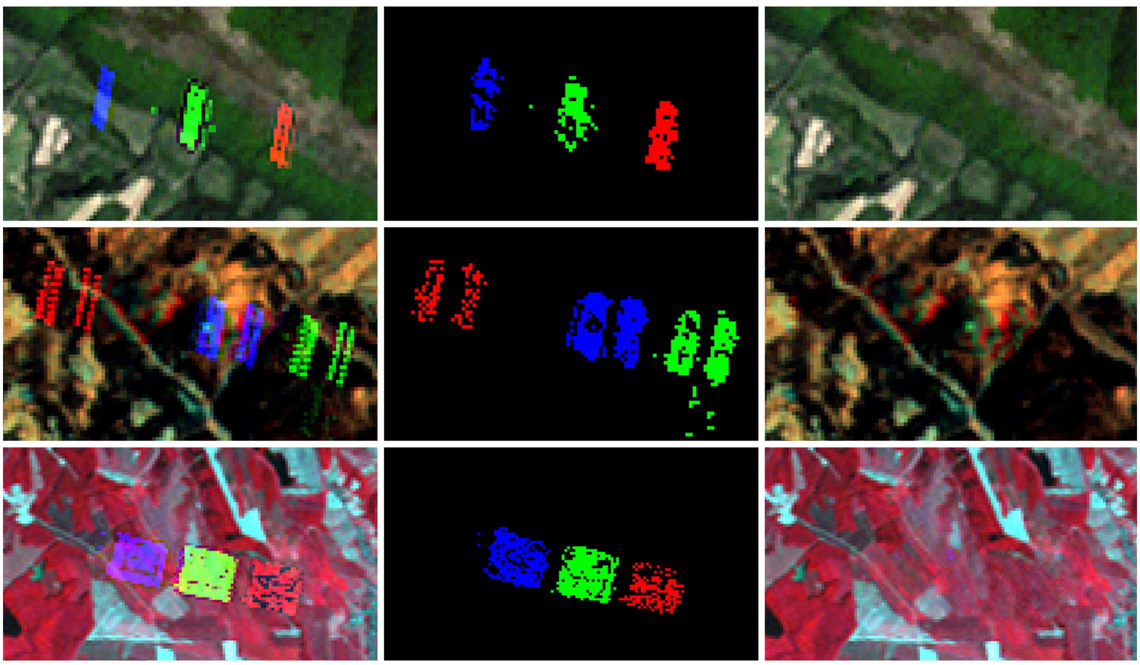

Figure B-2: Three examples of distorted areas occurring in a Landsat TM image (left), flagged pixel values after the detection procedure (middle) and the corrected image after locating similar pixels using a spectral matching operation and then substituting the erroneous band values (right). Band combinations for red, green, and blue are: 3/2/1 (top), 4/5/3 (middle), and 4/3/2 (bottom).

Validation based on artificially distorted pixels revealed very low average deviations, low standard deviations and narrow confidence intervals (Table B-2). Mean deviations were higher in the near infrared band (TM band 4) due to the high variability of vegetated areas in this spectral domain. For the imagery used in this study, the mean uncertainty level was lower than 2 digital numbers (~0.5% reflectance). The confidence intervals revealed that uncertainty connected to the mean estimation based on the sample of artificially distorted pixels was negligible. RMSE values confirmed that the vast majority of the corrected pixels displayed deviations between original and corrected band values that were much lower than the sensor's inherent noise level (estimated by Minimum Noise Fraction images over water bodies (Table B-2). The statistical analyses also suggested that distorted band values do not over- or under-saturate in most cases.

Table B-2: Statistical comparison of original and corrected spectra of artificially introduced distortions (Min / Max / Mean = minimum, maximum and average deviation of original and corrected spectra; STD = standard deviation; n = sample size; CI_L / CI_U = lower and upper limits of confidence intervals for $p < 0.01$; all values are given in digital numbers).

Band	*n*	*Min*	*Max*	*Mean*	*STD*	*RMSE*	CI_L	CI_U
1	1,702	0	15.00	0.35	1.06	0.60	0.29	0.42
2	1,812	0	12.00	0.19	0.62	0.44	0.16	0.23
3	2,368	0	15.00	0.43	1.19	0.65	0.36	0.49
4	559	0	15.52	1.14	2.92	1.07	0.82	1.45
5	772	0	15.78	0.78	2.18	0.88	0.57	0.98
6	1,904	0	15.52	0.46	1.40	0.68	0.38	0.55

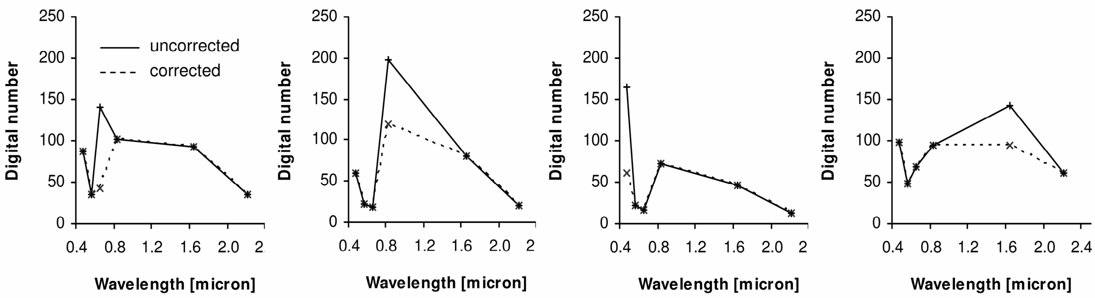

Figure B-3: Examples of spectra with erroneous band values before and after the correction. The deviation between uncorrected and corrected spectra is substantial and the correction algorithm results in more useful spectra (for details refer to text). All spectra were taken from a Landsat (5) TM image acquired 4th July 1994.

The methodology proposed in this research was highly effective in removing the missing pixel distortions for subsequent digital change detection. The artifacts were effectively removed from NDVI images and Tasseled Cap indices (Figure B-4). Even large clusters of distorted pixels were corrected, and the methodology restored textural information underlying the distorted areas, which can be important for applications that rely on continuous information on landscape heterogeneity (St-Louis et al. 2006), or for visual image analysis. Comparing the forest change maps for the three change detection methods reveals that the change maps differ substantially, because simple methods such as image differencing often results in noise in the change map. However, the change maps derived from disturbed images always label the missing pixel distortions as (pseudo-)change, thus underpinning the need to account for these distortions prior to digital change detection. After correcting the error-prone images, the missing pixels no longer appear as pseudo-change in the change maps for all three approaches (Please note that fewer missing pixels artifacts appear in the NDVI change map, because only two bands are used to derive the NDVI values, Figure B-5). The correction algorithm thus clearly mitigates and solves the single-band missing pixels problem for subsequent change analysis (Figure B-5).

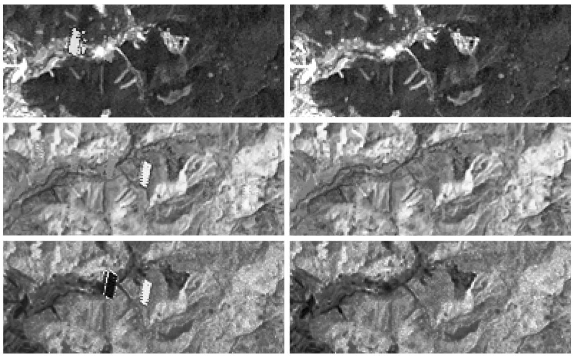

Figure B-4: Comparison of raw image data, NDVI, and Tasseled Cap indices for uncorrected (left) and corrected (right) images. The missing pixel distortions are not visible in the corrected images, thus allowing for better visual interpretation. All operations were carried out on a subset of a Landsat (5) TM image, acquired 4th July 1994, that displayed single-band distortions.

The methodology pursued in this research was limited to distortions that only occur in a single-band for a given pixel. Distorted pixels that display erroneous values in more than one band remained unprocessed. However, analyses of such pixels revealed that for the images used in this study, only a very small number of pixels (a maximum of 70 pixels for a full scene) were affected and hence the effect seems to be negligible. Our method can only detect distortions where the difference between the missing pixel's value and its surrounding is large enough to be picked up by edge operators. Yet, subsequent image analysis such as digital change detection will not be hindered considerably by distortions that only slightly deviate from their neighborhood.

The Laplacian operator detected errors in the NIR band less precisely, because the Roberts operator in combination with the subsequent band ratio comparison proved to be more sensitive to subtle deviations in digital numbers. This was due to the low level of collinearity of the NIR band to other bands which in inhibited the use of band ratios. As a consequence, some single-band missing pixel distortions in the NIR band may remain undetected, although visual examination and the tests with artificial data did not suggest lower detection rates for the NIR band compared to the other bands. Using a wider buffer in the selection routine for single-band missing pixels in the NIR would be a possible approach to ensure that all distorted pixels are processed.

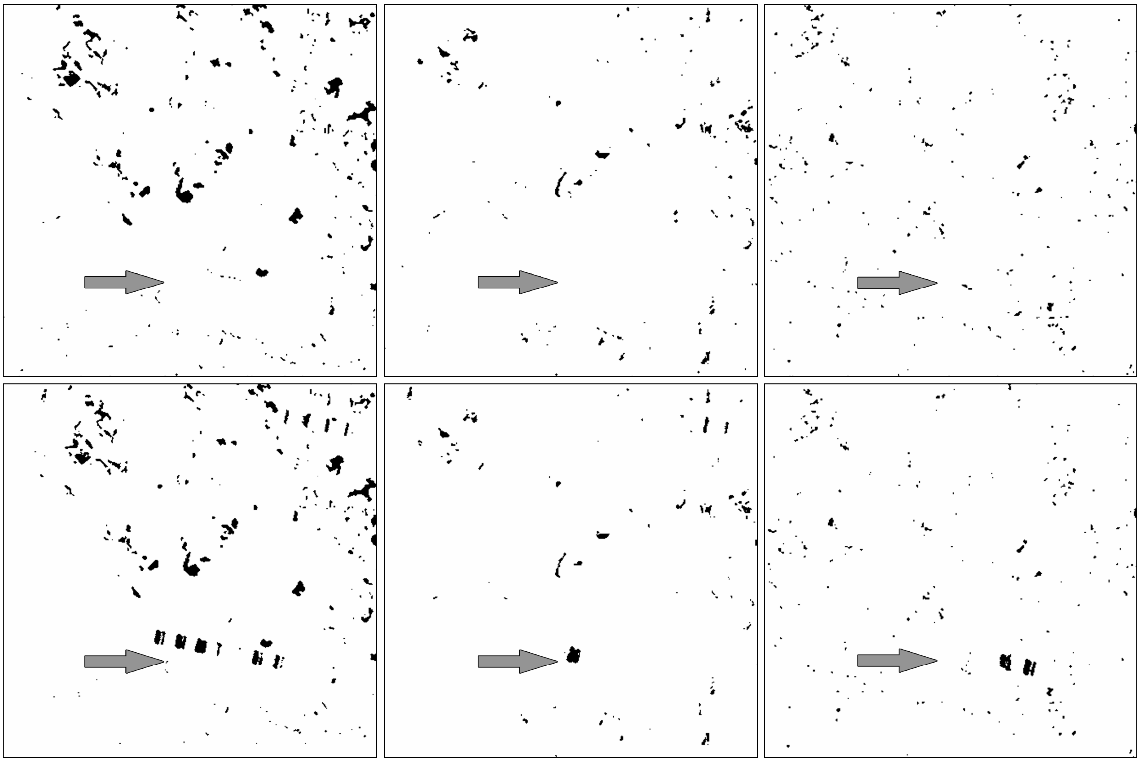

Figure B-5: Change maps (no-change / change) for different change detection methods before (bottom) and after (top) the correction of single-band missing pixels. All analyses were carried out on the image from 7th June 1994 that had ~65,400 distorted pixels. Image ratioing (left), NDVI difference image (middle), and the disturbance index (right) were calculated for a forested region in the Ukrainian Carpathians. The forest change maps differ considerably for different change detection methods. However, the missing-pixels distortions appear as pseudo-change for all approaches when relying on uncorrected images. The correction method removes the pseudo-change from the change maps (for details refer to text).

The search area of 100x100 pixels used in this study potentially limits the correction of single-band missing pixels in cases where no matching spectrum is found in the local neighborhood. This possibly explains some outliers that existed in the statistical summary (e.g. maximum deviation of up to 15 digital numbers, Table B-2). Possible solutions include implementing a maximum threshold criterion for RMS_{min} (a correction is only carried out if an undisturbed spectrum with an RMS_{min} below a specified threshold exists), or increasing the search neighborhood (which would significantly increase the processing load).

While our method was developed to correct missing pixel distortions in Landsat TM and ETM+ images, the program is not limited to these data. Generally, distortions found in all kinds of multispectral imagery can be corrected, as long as the distortions occur in a single band and enough undistorted bands remain for the RMS calculation (to select the best undistorted spectrum). Neighborhood operations have significant potential to correct or mitigate other types of distortions, too (e.g. multiband artifacts), and future research is needed to explore these possibilities.

5 Summary and Conclusions

Single-band missing pixels in Landsat TM and ETM+ datasets are relatively frequent and can tremendously hinder subsequent image analyses such as digital change detection. The software developed in this research implements a method to detect such pixels using edge operators. Using a least squares spectral matching algorithm, the distorted spectrum is compared to undisturbed spectra in the local neighborhood and the undisturbed spectrum of best fit is determined. The erroneous band value is then replaced with the corresponding value from the undisturbed spectrum.

The procedure proved to detect the affected pixels effectively. The correction yielded useful spectra and distorted areas were removed from the image. Validation of the correction algorithm using artificially distorted areas revealed that the mean deviation of original and corrected spectra was around 1 digital number and therefore well below the inherent noise level of Landsat TM imagery. Three different change detection methods carried out on uncorrected and corrected data showed that the correction prevented the missing pixels distortions from resulting in pseudo-change. The correction approach is thus a useful pre-processing step to mitigate the effect of single-band image distortions for digital change detection.

The software, programmed in IDL 6.0 (RSI 2003) and equipped with a graphical user interface, its source code, and a user guide are available free of charge to the remote sensing community via the webpage of Computers & Geosciences (www.iamg.org/

CGEditor) and the webpage of the Geomatics Department of Humboldt-Universität zu Berlin (www.hu-geomatics.de).

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